Investigating Effects of Out-of-Stock on Consumer SKU Choice

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Abstract

Out-of-stock (OOS), i.e., unavailability of products, is commonly observed in retail environment of the consumer packaged goods, but there have been few empirical studies regarding the effects of OOS on consumer product choice due to the lack of data on OOS incidents. In this paper, we study the effects of OOS on consumers' SKU preference and price sensitivity using a unique data set from multiple consumer packaged goods categories with information on recurring OOS incidents.

We obtain several substantive findings: (1) consumers' price sensitivity tends to be under-estimated when product unavailability due to OOS is not accounted for in discrete choice model; (2) in categories with a high level of SKU share concentration, consumer preference for a SKU is reinforced when facing OOS of other similar-in-attribute, familiar SKUs; and (3) in categories characterized by short inter-purchase time, consumer preference for a SKU is attenuated when it is frequently stocked out. The underlying reasons behind these findings are discussed with support from additional household-level analysis. We also illustrate that our findings can help retailers to evaluate the effect of OOS on category revenue and predict time-varying market shares of SKUs in periods following OOS incidents.

Keywords: Out-of-Stock, SKU Preference, Price Sensitivity, Category Management, Retailing

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Introduction

One of the key challenges for retailers is to keep products that customers want and need in stock.[1] Temporary product out of stock (abbreviated OOS for the rest of the paper) is commonly observed in grocery retailing. A study conducted by the Grocery Manufacturers of America, which surveyed 71,000 consumers in 661 retail outlets, found that the average out of stock rate[2] in a grocery category is 7.9%, and it costs retailers 4% loss in category sales. Out of stock is also reported as a top concern among retailers in Asia, Europe, and Latin America (Gruen, Corsten, and Bharadwaj 2002). Given the prevalence of OOS, an important question that arises is how consumers respond to frequent and recurring OOS when making purchase decisions.

Despite the importance of understanding consumer response to recurring OOS, there have not been many studies on this topic due to the unavailability of high quality data with OOS information. Some recent studies (Bruno and Vilcassim 2007; Musalem, Olivares, Bradlow, Terwiesch, and Corsten 2008) have focused on developing methods to capture the effect of OOS into brand choice models when OOS information is unobservable. In contrast, an advantage of this study is that we have detailed data on recurring OOS across multiple consumer packaged goods (CPG) categories, which allows us to carry out an in-depth investigation of the impact of OOS on consumers' SKU choices and the resultant implications to retailers.

[1] In 2001, the number of SKUs in an average grocery store was nearly 25,000; while in 2008, it has proliferated to 45,000, according to Food Marketing Institute.

[2] The out of stock rate is the percentage of SKUs that are out-of-stock in a store at a given time point. .

Specifically, we ask the following research questions: (1) How is a consumer's choice of a SKU affected by the SKU's past OOS, and by the OOS of other SKUs? (2) How are the OOS effects moderated by consumer demographics, purchase patterns, and characteristics of product categories? And (3) what is the impact of ignoring OOS information on estimates of consumer price sensitivity? To address these research questions, we develop an empirical model that captures multiple impacts of product OOS on consumer SKU choice.

First, we take into account in our model the effect of OOS on consumers' choice set (Hauser and Wernerfelt (1990); Roberts and Lattin (1991)). Without OOS information, marketing researchers have typically assumed that all choice alternatives are available to consumers in all purchase occasions. With recurring OOS information, we can explicitly adjust consumers' choice set based on product availability and investigate the implications of this adjustment on the estimation of model parameters, such as price and state-dependence coefficients. We can expect that, for example, if the frequency of OOS is correlated with price promotion, the estimates of price coefficient as well as own and cross price elasticity will be biased without the adjustment of the choice set based on the OOS information.

Second, we investigate how consumer preference towards a SKU is affected by its own past OOS and other SKUs' OOS. Behavioral research has shown that consumers can have a positive or negative reaction towards a product's OOS (Fitzsimons 2000), which may affect the subsequent choice of that product once it becomes available again. We call this the *inter-temporal effect of OOS*. Besides this, consumer preference towards a product may be affected by the OOS of other products in the same category, which we call the *contextual effect of OOS*. Such an effect can be channeled by the similarity between the OOS SKUs and the SKU in consideration. For example, in some occasions the unavailability of some products might cause a consumer to buy a SKU with similar attributes, while in other occasions the consumer might decide to try product varieties which are dissimilar in attributes. In addition, it is likely that given the same level of product attribute similarity, the OOS of products that a consumer is more familiar with will have larger contextual effects than those of less familiarity. This is consistent with Fitzsimons (2000), which suggests that the OOS effect is moderated by consumer's commitment to the OOS brand. Thus, in our model we allow the contextual effect of OOS to be moderated by the similarity between the focal SKU and the OOS SKUs as well as by consumers' familiarity of the OOS SKUs.

We apply our model to six product categories. Our estimation results show that taking into account of recurring OOS significantly improves model performance and corrects estimation bias. In particular, new to the literature of OOS effects in the context of consumer choice model, we find that: 1) consumer price sensitivity estimates are under-estimated without recurring OOS information, and this is consistent across the six product categories we investigated; 2) the inter-temporal effect of OOS is negative in categories characterized by short inter-purchase time; 3) for the contextual effect of OOS, we find that in categories with high market share concentration, consumer preference for a SKU increases with the OOS of SKUs which are similar in attributes to the focal SKU, but the result is opposite in categories with low market share concentration.

As an important feature of our research, we further conduct a *within*-category analysis which links household specific reaction to OOS with each household's purchase pattern in each of the six categories. The purpose of this analysis is to gain additional insights on the relationships between the inter-temporal and contextual effects of OOS and consumer purchase patterns. This analysis is feasible because we have household level purchase data and detailed information on OOS at the SKU-level. Similar to findings from the cross-category analysis, for the inter-temporal effect of OOS, we find that households with shorter inter-purchase time react more negatively to a SKU for its past OOS. As to the contextual effect of OOS, we find that for households who have a high (low) purchase share concentration, their preference for a SKU increases (decreases) when similar SKUs are out of stock.

To obtain further managerial insights from our study, we also carry out a series of counterfactual analyses based on our estimation results to investigate the impacts of OOS on SKU- and category-demand. The results suggest that both the inter-temporal and contextual effects of OOS have significant impacts on SKU- and category-level revenues. We also find that eliminating all OOS incidents in the categories studied leads to on average a 2.7% increase in category sales. However, the impacts of OOS on category sales differ across categories. In a category (e.g. ketchup) where the contextual effect of OOS is positive, we find that eliminating all OOS may actually lower the category sales. Those analyses imply that retailers should consider both the inter-temporal and contextual effects of OOS when making decisions that affect the occurrence of OOS, and those decisions have to be category specific.

Our study contributes to the consumer choice model literature by incorporating the effects of OOS into a choice model and revealing some significant moderators of the OOS effects. Among the limited number of studies on the effects of OOS on consumer preference and product demand, Fitzsimons (2000) investigated consumer response to a brand's OOS in a laboratory setting. Similar to his study, we adjust the size of consumers' choice set with OOS information and examine the effect of a SKU's past OOS on its demand, i.e., the inter-temporal effect, in our empirical analysis. In addition, we model and estimate the contextual effect on consumer choice. Campo, Gijsbrechts, and Nisol (2003) studied the impact of OOS on consumers' purchase incident, brand choice and purchase quantity. Due to the lack of actual OOS information, they had to infer OOS incidents from each SKU's sales pattern, which was prone to inaccuracy and might affect the resultant inference on the effects of OOS. Kalyanam, Borle, and Boatwright (2007) used quarterly sales data on men's shirt and aggregate-level OOS information to study the effects of an item's OOS on its own sales, as well as the sales of other items. We develop a discrete choice model to study similar research questions with household-level purchase data and OOS information at each shopping occasion, and find that reaction to OOS is related to consumer purchase patterns and the characteristics of product categories. Most recently, Bruno and Vilcassim (2007) and Musalem et. al. (2008) developed empirical methods to incorporate OOS effects into consumer choice models when detailed information on OOS incidents is not available. Our study sets apart from theirs by focusing on investigating the inter-temporal effect and the contextual effect of OOS and understanding the effect of incorporating OOS information on consumer price sensitivity inference with detailed OOS information available to us.

Several studies have examined the effects of SKU reduction by employing experimental and survey data (Broniarczyk, Hoyer, and McAlister 1998) or transaction data with one-time permanent assortment reduction (Boatwright and Junes 2001, Borle et. al. 2005, Zhang and Krishna 2007). Our research differs from this stream of literature as we study the effects of recurring and temporary OOS instead of those of one-time SKU reduction. Using recurring and temporary OOS data, we are able to provide measures of the inter-temporal effect of OOS on consumer choice of a SKU. Our attribute-based specification also allows us to understand the contextual effect of OOS on the focal product.

The rest of the paper is organized as follows. In the next section, we present our empirical model which accounts for the effect of OOS on choice set as well as the inter-temporal and contextual effects of OOS on consumer preference. In the following sections, we describe the data, present the estimation results, and discuss the managerial implications of our study. We conclude the paper in the final section and suggest the directions for future research.

Model

We model SKU demand using a household-level random-coefficients multinomial logit model (Chintagunta, Jain, and Vilcassim 1991). In order to take into account of the fact that consumers face product stock-out during some of their shopping occasions, we modify the usual MNL model in several ways.

During each purchase occasion, a household chooses from a set of J SKUs. Without information on product stock-outs, researchers typically assume all SKUs are available to the household at all purchase occasions. However, when a SKU is unavailable to the household during a shopping occasion, it cannot enter its choice set. Therefore, we need to allow consumers' choice set to vary across different shopping occasions. When some SKUs are stocked out during a purchase occasion, the probability of a household h $(h = 1, 2, ..., H)$ purchasing one of J available SKUs (denoted by $j = 1, 2, ..., J$) or not purchasing in the category ($j = 0$) on a shopping occasion $t_h = 1, 2, ..., T_h$ is given by:

$$\theta_{hjt_h} = \frac{\left(1 - OOS_{hjt_h}\right)\exp\left(v_{hjt_h}\right)}{\exp\left(v_{h0t_h}\right) + \sum_{k=1}^{J}\left(1 - OOS_{hkt_h}\right)\exp\left(v_{hkt_h}\right)} \tag{1}$$

where OOS_{hjt_h} is a dummy variable that takes the value 1 if SKU j is out of stock at the shopping occasion t_h of household h, and takes the value 0 if it is available. The mean utility for household h to purchase SKU j at shopping occasion t_h, v_{hjt_h}, is given by

$$v_{hjt_h} = \beta_h \cdot X_j - \beta_{ph} \cdot p_{jt_h} + SD_h \cdot sim_{l_h j} + \gamma_{h1} \cdot OOS_{hj,t_h-1} + \gamma_{h2} \cdot \sum_{k=1,k\neq j}^{J} OOS_{hkt_h} \cdot sim_{kj} \cdot cum\_share_{hkt_h}. \tag{2}$$

And the mean utility for household h to purchase the outside good at shopping occasion t_h is $v_{h0t_h} = \delta_h \cdot INV_{ht_h}$, where INV_{ht_h} denotes the (mean-centered) product inventory held by household h at shopping occasion t_h, while δ_h denotes the corresponding inventory coefficient.

There are five terms in equation (2). The first term, $\beta_h \cdot X_j$, captures the intrinsic preference of household h towards SKU j, where X_j is a vector of attributes of SKU j (Fader and Hardie 1996) and β_h is the corresponding set of coefficients. The second term in equation (2) captures household h's response to the price of SKU j with p_{jt_h} denoting the retail price of SKU j at shopping occasion t_h and β_{ph} denoting the corresponding household level price coefficient.

The third term in equation (2), $SD_h \cdot sim_{l_h j}$, captures the state-dependent behavior (Seetharaman, Ainslie and Chintagunta 1999) of household h with $sim_{l_h j}$ denoting the similarity between SKU j and the SKU l_h bought by the household in the last purchase occasion and SD_h as the corresponding coefficient. $sim_{l_h j}$ is defined as

$$sim_{l_h j} = \frac{I_{l_h j} + \sum_{m=1}^{M} r_m \cdot I_{l_h j,m}}{1 + \sum_{m=1}^{M} r_m}, \tag{3}$$

where l_h refers to the SKU that household h bought in the last purchase occasion, M stands for the number of product attributes represented among all SKUs within the product category, $I_{l_h j}$ is an indicator variable that takes the value 1 if $l_h = j$, i.e., l_h and j are the same SKU, and 0 otherwise, $I_{l_h j,m}$ is an indicator variable that takes the value 1 if SKUs l_h and j share attribute m and 0 otherwise, and $r_m > 0$ [3] stands for the perceived importance for attribute m in determining inter-SKU similarity. Note that $sim_{l_h j}$ is restricted to lie between 0 and 1, and is monotonically increasing in the number of attributes shared by SKUs l_h and j. This specification of $sim_{l_h j}$ and the approach of modeling state-dependent behavior is similar to that in Che, Sudhir, and Seetharaman (2006).

The fourth term in equation (2), $\gamma_{h1} \cdot OOS_{hj,t_h - 1}$, reflects the impact of SKU j's OOS encountered by household h during her past shopping occasion on her current preference towards j. $OOS_{hj,t_h - 1}$ is an indicator variable that takes the value 1 if SKU j is out of stock on consumer h's last shopping occasion t_h, and γ_{h1} is the corresponding

[3] In estimation, we specify $r_m = \exp(\phi_m)$ and report ϕ_m in the results.

coefficient. This term captures the inter-temporal effect of past OOS of a SKU on consumer preference for the product. When a SKU is stocked out in the last purchase occasion, it might affect consumer preference and subsequently its current-period purchase probability in an either positive or negative way (Fitzsimons 2000). It is worth noting that this effect is different from another dynamic effect in our model: the state dependence of consumer SKU choice, as reflected by the third term in equation (2). The latter captures the effect of consumer past consumption experience on the current-period SKU preference.

The fifth term in equation (2), $\sum_{k=1}^{J} OOS_{hkt_h} \cdot sim_{kj} \cdot cum\_share_{hkt_h}$ is a measure that summarizes the impact of the current-period OOS of different SKUs on the focal SKU. When a SKU k is out of stock in the current period, OOS_{hkt_h} takes on the value of 1 (otherwise 0), and it is weighted 1) by its similarity, sim_{kj}, to the focal SKU j; and 2) by the household h's purchase share of this SKU up to t_h, $cum\_share_{hkt_h}$. Then we sum up the calculated measures over all SKUs. sim_{kj} is a similarity variable that captures how much perceived similarity SKU j has to the OOS SKU k, and is operationalized in the same way as in the third (state-dependence) term. $cum\_share_{hkt_h}$, the household h's purchase share of the OOS SKU k up to time t_h, reflects the household's familiarity for the OOS SKU. Overall, this fifth term in equation (2) captures the contextual effect of OOS.[4] This effect can be either positive or negative, depending on the coefficient, γ_{h2}.

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[4] An alternative way of modeling the contextual effect of OOS is to add all the OOS SKU dummies directly into equation (2). This will involve a large number of parameters to be estimated. The measure variable we constructed for capturing the contextual effect of OOS is a parsimonious one. In addition, it allows for the

To complete the model specification, we allow model parameters to be household-specific. Specifically, we let

$$\begin{pmatrix} \alpha_{hj} \\ \beta_{ph} \\ \beta_h \\ \gamma_{h1} \\ \gamma_{h2} \\ SD_h \\ \delta_h \end{pmatrix} = \begin{pmatrix} \alpha_j \\ \beta_p \\ \beta \\ \gamma_1 \\ \gamma_2 \\ SD \\ \delta \end{pmatrix} + \sum \nu_h, \qquad \text{where } \nu_h \sim P_\nu^*(\nu) \tag{4}$$

We accommodate unobserved heterogeneity across households by allowing household-specific parameters to follow normal distribution across households (Gonül and Srinivasan, 1993), with ν_h representing unobserved household-specific characteristics, which are assumed to follow a standard multivariate normal distribution, $P_\nu^*(\nu)$, and Σ being a vector of parameters for unobserved heterogeneity.

Given equations (1)-(4), the log-likelihood function of consumer SKU choices according to our model can be written as,

$$LL = \sum_{h=1}^{H} \log \sum_{t_h=1}^{T_h} \int_{\nu_h} \sum_{j=1}^{J} \left[\theta_{hjt_h}(\nu_h)\right]^{I_{hjt_h}} f(\nu_h)\, d\nu_h \tag{5}$$

where I_{ijt_h} =1 if *j* is chosen by household *h* at shopping occasion t_h; and 0 otherwise. To estimate the model parameters, we adopt the simulated maximum likelihood approach (SML) to maximize the value of the log-likelihood function as equation (5) requires the evaluation of a high-dimensional integral.

We describe the data used for our estimation in the next section.

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effects of the OOS SKUs on the demand of a focal SKU to be based on their similarity to the focal SKU and consumers' familiarity to the OOS SKUs.

Data Description

We use scanner panel data from a large national grocery chain on household purchases of SKUs between May 2005 and May 2007 in *one* store in the San Francisco Bay area. The store is located in a mountain area, and has no other large grocery competitors (stores from other retailers or from the retailer itself), or grocery supercenters (e.g. Target or Wal-Mart) within a 5-mile radius. One possible outcome of OOS in multiple categories is that consumers could switch stores due to unfavorable assortment perception of a store. Using data from one store which has no competing stores nearby helps to reduce the possible bias from ignoring the effect of OOS on store choice. We select categories based on two criteria: 1) they each have a reasonable number of OOS occurrences, and 2) households do not typically buy multiple SKUs in one purchase occasion. This leads us to select the following six product categories: Ketchup, Tissue, Tuna, Orange Juice, Bacon, and Laundry Detergent (Liquid). Summary statistics of the prices, market shares, and brand-level average OOS frequencies in these six categories are given in Table 1.

~Table 1 About Here~

Our OOS dataset is recorded systematically by the retailer on a daily basis, and we append it to the household transaction dataset.[5] Brand-level OOS in the 4th column of Table 1 is the average frequency of a brand's OOS across consumers' shopping trips. In the 5th column of Table 1, we calculate the correlation between brand market shares and OOS frequencies. We find there is a very high positive correlation between the brands'

[5] We discuss the procedure of appending OOS observations to transaction dataset later in the text.

market shares and their OOS frequencies. Popular brands are more likely to be stocked-out during households' shopping occasions.

An important research question we try to answer in this study is the effect of OOS on consumer price sensitivity. If OOS takes place more often when the SKUs are on sale, ignoring OOS information will distort researchers' inference of consumer own- and cross- elasticity of price. For this reason, we further investigate the relationship between OOS and price promotion, as shown in Table 2.

~Table 2 About Here~

We find that a high percentage of OOS takes place when a SKU is on sale. Among them, Orange Juice has the highest percentage of OOS (89%) that takes place under price promotion. We also find OOS is more likely to occur when price cuts are deep. For the weeks that both OOS and price promotion were observed, the average price cuts ranged from 19.2% (Tissue) to 37.9% (Orange Juice). In contrast, for the weeks that price promotion was observed but there was no OOS, the average price cuts were only between 10.32% (Tissue) and 25.17% (Orange Juice). With this finding in mind, we further elaborate how the relationship between OOS and price promotion affects price elasticity estimates when we discuss the estimation results of the model.

The scanner-panel data also contains information of all the transactions by the store loyalty card holders,[6] including transaction timing, SKU purchased, quantity, and price paid. From the panel of loyalty card holders, we select households who made at least 10 purchases each year (4 for ketchup) in each of the six categories. We follow the purchase selection procedure (Gupta, Kaul, and Wittink 1996) to retain households only

[6] The loyalty card is free to apply and guarantees a low price whenever it is shown to the cashier. Our data shows 98% of the transactions are done with the card, and we only include transactions from card members in our estimation.

purchasing the major SKUs in each category. From the retained set, we randomly select 100 to 200 households from each category to be in the estimation sample. The details of the household demographics data are given in Table 3.

~Table 3 About Here~

To investigate the effects of OOS on household SKU choice, we need to append the transaction dataset with trip-level SKU OOS information. From the store-level OOS dataset, we know the name of the OOS SKU on a given day, the recorded OOS time, and the transaction time of the last unit sold before OOS. We summarize the OOS data of the six categories in Table 4.

~Table 4 About Here~

On average, recorded OOS time in the six categories is 6pm in the evening, which is consistent with information obtained from our conversations with the store managers. The actual OOS time could be earlier than the recorded OOS time. We classify households' shopping trips that took place between the last unit of a SKU purchased before the recorded OOS time and the recorded OOS time of a SKU as trips subject to the OOS of this SKU. In Table 4, we report the average time intervals between the recorded OOS time and the last purchase before the recorded OOS time across SKUs for each category. We find that the intervals are between 5 to 14 hours across the six categories.

After the recorded SKU OOS time and before the replenishment (which could happen hours before the first purchase after OOS), the shopping trips in the category are also subject to the OOS of that SKU. From our conversations with the store managers and observations from actual store visits, we learned that the replenishment usually takes place around midnight in the store. In the transaction dataset, as reported in Table 4, we also find that the first purchase of an OOS SKU in each of the six categories took place 12 hours after the recorded SKU OOS time, which seems to confirm that replenishment does happen over midnight. Therefore, we assume all the replenishments happen at 12AM and classify the shopping trips that took place between the recorded SKU OOS time and 12 AM the next day as trips subject to the OOS of that SKU.[7]

With the above criteria, we identify each household's shopping trips that were subject to OOS and this allows us to study the effects of OOS on consumer SKU choice decision.

We conduct the estimation of our model described in the last section using the data described here. The results are reported and discussed in the next section.

Empirical Results

To disentangle the multiple effects of OOS on consumers' SKU choices, we start with estimating three different versions of our proposed model as summarized in the following table. For the convenience of exposition, we drop subscript *h* here and in the following text.

	Model 1	Model 2	Model 3
OOS products excluded from choice set	No	Yes	Yes
Inter-temporal effect (γ_1)	No	No	Yes
Contextual effect (γ_2)	No	No	Yes

Model 1 is the standard multinomial logit model used in the marketing literature, while models 2 and 3 take into account of OOS effects on choice set and on SKU

[7] There is no shopping trip between 12am and 6am in our estimation samples across six categories.

preference. Comparing the performance of models 1 and 2 helps to illustrate the effects of OOS on choice set, and comparing the performance of models 2 and 3 shows the consequences of OOS on SKU preference, above and beyond its effect on choice set.

The fit statistics of the above three models are shown in Table 5.

~Table 5 About Here~

Based on the fit statistics – Log-Likelihood (*LL*), Akaike Information Criterion (*AIC*) and Schwarz Bayesian Criterion (*SBC*) – for each of the 3 versions of our proposed model mentioned above, we observe that the full model (Model 3) outperforms the other two models. This shows the importance of accounting for the effect of OOS on consumer choice set as well as its effect on SKU preference. Comparing the parameter estimates of these three models across six categories, we find that accounting for OOS information does have important implications on the estimates of price sensitivity, SKU preference and other parameters of consumers' utility. Below we present these findings in details.

The Effect of OOS on Price Coefficients

The first finding we have across the six categories is the effect of OOS on the estimates of the price coefficient, as shown in Table 6.

~Table 6 About Here~

We find, after accounting for the effect of OOS on choice set and SKU preference, the estimates of price coefficient increase in magnitude. We also calculate the average own price elasticity across brands in each category, and it reveals a similar pattern. The price elasticity measures from Model 3 (the full model) are 2%~12% larger in magnitude than those from Model 1 (the model without OOS). This result suggests that *consumers' price sensitivity tends to be underestimated when the effects of OOS are* *ignored.* To our best knowledge, this result regarding the effect of ignoring OOS information on the estimation of consumers' price sensitivity has not been documented in the previous empirical studies.

The descriptive information on OOS occurrence as reported in Table 2 can help us to understand to underlying reason behind this result. From Table 2, a high percentage of OOS incidences are associated with price promotion, and OOS is also more likely to occur when the price cut in promotion is deeper. When a product is stocked out, consumers have to either switch to buy another product or not buy. Therefore, in the absence of OOS information, consumers' price sensitivity would be underestimated as researchers only observed that consumers were buying the products what were regular priced (or not buying) instead of buying the products on sale.

The Inter-temporal and Contextual Effects of OOS on SKU Preference: Cross-Category Analysis

In Table 7 we present the estimates of γ_1 and γ_2 from Model 3, the full version of our proposed model.

~Table 7 About Here~

As described in the model section, γ_1 captures the inter-temporal effect of past OOS of a SKU on consumers' preference to it, while γ_2 captures the contextual effect of other SKUs' OOS on the focal SKU.

We find that the estimates of γ_1 are 1) negative and significant for the Orange Juice and Tuna categories and ii) positive but insignificant for the Bacon, Ketchup, Laundry Detergent, and Tissue categories. Since γ_1 captures the lag effect of a SKU's past OOS on consumer preference of the product, we conjecture that the differences in the estimates of γ_1 across categories are related to consumers' average inter-purchase time in different categories. Column 3 in Table 7 presents the average inter-purchase time in the six categories. We find households' inter-purchase time is shorter in the Orange Juice and Tuna categories compared to the other four categories. This provides a possible behavioral explanation for the negative and significant estimates of γ_1 in these two categories: since consumers buy orange juice and tuna much more frequently than other products, e.g. ketchup, they tend to have better short-term memories of the past OOS occurrence in these two categories, and this in turn may reduce their current preference for those SKUs found to be out-of-stock in the previous shopping occasion. It is interesting to note that while we find significant inter-temporal effect of OOS on consumer SKU preference, we do not find that OOS results in any significant changes in the estimates of the state dependence parameters across the three models.[8] An important difference between the inter-temporal effect of OOS on consumer SKU preference and the state dependence of consumer's SKU level utility, as modeled in equation (2), is that the former depends on whether a consumer was *exposed* to a SKU in the past shopping occasion and the latter depends on whether a consumer actually *purchased* a SKU when she bought the product category most recently.

The estimates of γ_2 measure the contextual effect of OOS. We find that the estimates of γ_2 are positive and significant for Ketchup and Tuna categories, while they are negative and significant for the Bacon, Laundry Detergent, Orange Juice, and Tissue categories. A positive (negative) γ_2 indicates that when OOS products are (1) more similar, in terms of attributes, to the focal product; and (2) more familiar to consumers in terms of higher purchase shares, consumer preference for the focal SKU is *reinforced*

[8] Due to space constraint, the estimation results of all parameters of the three models in each of the six categories are presented in a technical appendix available upon request from the authors.

(*attenuated*) in the face of OSS of those products. To provide an explanation to this finding, we conjecture that the different patterns of γ_2 across categories are related to the share concentration of SKUs within each category. The intuition is the following. When a category is characterized by a small number of SKUs with high market shares, consumers might view the non-OOS SKUs, which are similar to the OOS SKUs in product attributes, as becoming more "precious" due to scarcity of other alternatives in the category (Lynn 1991). In contrast, when a category consists of a large number of SKUs each with small market share, consumers might attribute the OOS of these SKUs to being "undesirable" so that they were not sufficiently stocked in the category. Therefore, consumers in this case might favor SKUs that are dissimilar to the OOS ones.

In order to validate the above conjecture, we calculate the Herfindahl indices, defined as the sum of squares of market shares of all SKUs, in each of the six categories. A high value of Herfindahl index indicates high concentration of SKUs in a category. Column 4 in Table 7 lists the Herfindahl index measures for the six categories. We can see that Ketchup and Tuna belong to one group, which has high values of Herfindahl index, while Bacon, Landry Detergent, Orange Juice, and Tissue belong to the other group, which has low values of Herfindahl index. Clearly, our results show that higher values of Herfindahl index are associated with higher estimated values of γ_2. Thus, our conjecture is supported.

The Inter-temporal and Contextual Effects of OOS on SKU Preference: Within-Category Analysis

Our cross-category analysis has shown that the variations in the inter-temporal and contextual effects of OOS across the six categories we studied are closely related to the differences in consumer purchase patterns across those categories. If those findings from the cross-category analysis are general instead of being superficial, we should expect that similar relationship between the inter-temporal and contextual effects of OOS and consumer purchase patterns can be found in a within-category analysis. That is, we should expect a negative correlation between an individual household's γ_1 and her purchase frequency, and a positive correlation between her γ_2 and the Herfindahl index of her SKU-level purchase shares, regardless of which category she is purchasing from.

To test this, we carry out a within-category analysis in each of the six categories. Specifically, we first re-estimate Model 3, the full model, by allowing $\{\gamma_{h1}, \gamma_{h2}, SD_h, \delta_h\}$ to be household-specific and a function of household demographic variables (such as family size, income, etc.) ;[9] then we calculate the following measures for each household in each of the six categories: 1) the household-specific OOS parameters, $\hat{\gamma}_{1h}$ and $\hat{\gamma}_{2h}$, based on the estimates of model parameters and the household level demographics information; 2) household-specific Herfindahl index based on the specific household's SKU purchase shares, and 3) household-specific average inter-purchase time. Once we obtain these measures, we run two OLS regressions for each category *c*:

$$\begin{aligned} \hat{\gamma}_{1hc} &= \alpha_c + \beta_c \text{Interpurchase\_time}_{hc} + \varepsilon_{hc} \\ \hat{\gamma}_{2hc} &= \alpha_c^{'} + \beta_c^{'} \text{Herfindahl\_Index}_{hc} + \varepsilon_{hc}^{'} \end{aligned} \tag{6}$$

We expect that $\hat{\beta}_c > 0$ and $\hat{\beta}_c^{'} > 0$ if the findings from the cross-analysis also apply to the individual households within each category. Our estimates $\hat{\beta}_c$ and $\hat{\beta}_c^{'}$ for each of the six categories are reported in Table 8.

[9] The estimation results of this model across six categories are presented in a Technical Appendix available upon request from authors.

~Table 8 About Here~

Table 8 shows that in all of the six categories, the individual inter-purchase time coefficients (β_c) are positive and significant. It also shows that in five out of six categories individual Herfindahl index coefficients (β_c') are positive and significant. The only exception is the Orange Juice category, in which β_c' is also positive but insignificant. Thus, our within-category analysis lends strong support to the robustness and generalizibility of the findings obtained from the cross-category analysis. This implies that the relationship found between the inter-temporal and contextual effects of OOS and consumer purchase patterns is likely to have a solid behavioral foundation.

Managerial Implications

Our study so far has focused on understanding how recurring OOS may affect consumer's product choice. To illustrate the managerial implications of our study, we further conduct three counterfactual analyses using the estimates of our model parameters. The results are reported below.

In the first counterfactual analysis, we study the effect of OOS on brand-level[10] market shares by calculating the choice elasticities with respect to brands' OOS. In this exercise, we assume all households visit the store once a week and only purchase one unit. We first calculate market shares (denoted as s_{jt}^{0}) for a brand j $(j=1,\ldots, J)$ for 52 weeks assuming there is no OOS. Then we let brand j to be stocked out during the 10^{th} week, and re-calculate its market share for the remaining 42 weeks (denoted as s_{jt}^{1}). The

[10] For exposition purpose, our counterfactual analyses are done at the brand level. We define a brand-level OOS as the OOS of all its SKUs.

own OOS elasticity for brand *j* is defined as the percentage change in the cumulated sales for brand *j* due to its own OOS in a period of *T* weeks (we set *T=10*) following the OOS week, i.e.,

$$E_j^{j,oos} = \frac{\sum_{t=t_{j,oos}}^{t_{j,oos}+T-1}\left(s_{jt}^1 - s_{jt}^0\right)}{\sum_{t=t_{j,oos}}^{t_{j,oos}+T-1} s_{jt}^0}$$

Similarly, we calculate the cross OOS elasticity of brand *j*'s OOS on the sales of brand *i* (*i*≠*j*) as

$$E_i^{j,oos} = \frac{\sum_{t=t_{j,oos}}^{t_{j,oos}+T-1}\left(s_{it}^1 - s_{it}^0\right)}{\sum_{t=t_{j,oos}}^{t_{j,oos}+T-1} s_{it}^0}$$

We repeat the above steps for all brands in the category, and for all six categories. In the third column of Table 9, we report the average OOS elasticities across brands in these six categories.

~Table 9 About Here~

In the fourth column of Table 9, we report the average OOS elasticities when we set γ_2 equal to zero; and in the fifth column of Table 9, we report the average OOS elasticities when we set both γ_1 and γ_2 equal to zero. We then calculate and report the percentage changes in the estimates of the average OOS elasticities due to the effect of incorporating γ_2 and γ_1 respectively in the sixth and seventh columns.

Since γ_1 and γ_2 measure the effects of OOS on own and *other* brands respectively, we look at the estimates of own (cross) elasticities of OOS to understand the impact of γ_1 (γ_2). We find when incorporating γ_2, the cross elasticities of OOS for Ketchup and Tuna increase by 35.21% and 30.54% respectively. This indicates a strong positive cross brand switching effect and is consistent with the positive and significant γ_2 estimates in these two categories. We also find when incorporating γ_1, the own elasticities of OOS for Orange Juice and Tuna decrease by 15.7% and 4.13% respectively, which is again consistent with the negative and significant estimates of this coefficient in these two categories.

In our second counterfactual analysis, we are interested in the relationship between a brand's market share and the effect of its recurring OOS on category revenue. Note that observed data does not provide a reliable answer to this question due to the high correlation between market share and OOS frequency as shown in Table 1. Therefore a counterfactual analysis, in which the OOS frequency is controlled, is necessary. As in the first counterfactual analysis, we first calculate market shares for all brands assuming there is no OOS. Next we let OOS occur every 5 weeks in the 52-week period for a given brand. Then we use our model estimates to calculate the change of categories sales due to its OOS. We repeat this calculation for each brand in a category, and for all six categories. We illustrate the relationship between brand market shares and the impact of OOS on category sales in Figure 1.

~Figure 1 About Here~

The horizontal axis in each of the six graphs (one for each category) in Figure 1 is the brand market share when there is no OOS, while the vertical axis is the net impact (in percentage) of the recurring OOS of a given brand on the entire category revenue. Take Heinz in the Ketchup category as an example. Its sales account for 80% of the total category revenue and a recurring (every 5 weeks) OOS of Heinz would cause the category sales to decrease by 11.5%. Overall, our finding is consistent with Kalyanam, Borle, and Boatwright (2007), which used aggregate-level OOS information. We find that there is a very high correlation between a brand's market share and the impact of its OOS on category sales across all six categories. The higher a brand's market share, the larger loss in category sales as a result of its recurring OOS. More interestingly, we find in most of the case, OOS of small brands actually benefits the category sales, which implies that retailers could strategically use OOS of small brands to gain revenue.

In our last counterfactual analysis, we calculate the changes in category revenue if we eliminate all OOS incidents observed in different categories in our data. The results are presented in Table 10.

~Table 10 About Here~

We find that on average the retailer's loss in a category due to OOS is 2.72% of its total category revenue. This is quite consistent with the study done by Grocery Manufacturers of America (Gruen, Corsten, and Bharadwaj 2002), which found OOS on average cost a retailer 4% of loss in sales. In the world of retailing characterized by razor-thin profit margins, this is a sizable loss. Most interestingly, we find that failure to account for both γ_1 (inter-temporal effect) and γ_2 (contextual effect) can lead to an opposite inference with regard to the impact of OOS on category revenue. For example, if both the inter-temporal effect and the contextual effect OOS are ignored, eliminating all OOS incidents lead to a decrease in category revenue (-0.35%) in the Orange Juice category and an increase in category revenue (1.15%) in the Ketchup category. However, once we incorporate both effects, the changes reverse to positive (0.41%) in the Orange Juice category and negative (-0.41%) in the Ketchup category. This indicates the importance of accounting for both the inter-temporal effect and the contextual effect of OOS in conducting category management.

Conclusion

In this paper, we propose an attribute-based choice model that captures the effects of recurring OOS on household SKU preference and choice set. We estimate this model using household purchase data and recurring OOS observations in six categories. With this model, we gain an understanding of multiple effects of OOS on consumer SKU preference across different product categories. Specifically, we reveal the link between consumers' inter-purchase time and the inter-temporal OOS effect, i.e., the impact of past OOS of a SKU on consumers' preference toward it.; and the link between consumers' purchase concentration and the contextual OOS effect, i.e., the impact of other SKUs' OOS on consumers' preference toward a given SKU. Besides, we also show that consumers' price sensitivity tends to be under-estimated when product unavailability due to OOS is not taken into account in the discrete choice model. We illustrate in the counterfactual analyses how our findings can help retailers to evaluate the effect of OOS on category revenue, and predicting time-varying market shares of SKUs in periods following OOS.

Several directions exist for future research. First, it will be interesting to further explore the underlying behavioral process for the inter-temporal and contextual effects of OOS on consumer SKU preference revealed in both our cross-category analysis and within-category analysis. Controlled laboratory experiments could be desirable for this purpose. Second, we model the effects of OOS in a reduced-form way. It will be interesting to see whether frequent OOS of products may change consumers' expectations on product availability so that they may rationally adjust their inventory and consumption decisions accordingly. This calls for a dynamic structural modeling framework with forward-looking consumers, as in Erdem, Imai, and Keane (2002). Finally, our study uses information only from one store, which is not close to any competitors so that we can abstract away from the store switching issues. In reality, store switching due to OOS is not a trivial issue (Gruen, Corsten, and Bharadwaj 2002). Future research with data from multiple competing stores can study the effects of OOS with a more sophisticated model that incorporates consumers' store choice decisions.

References

Boatwright, Peter and Joseph C. Nunes (2001), "Reducing Assortment: An Attribute-Based Approach," *Journal of Marketing*, 65 (July), 50–63.

Borle, Sharad, Peter Boatwright, Joseph B. Kadane, Joseph C. Nunes, and Galit Shmueli (2005), "The Effect of Product Assortment Changes on Customer Retention," *Marketing Science*, 24 (4), 616–22.

Broniarczyk, Susan M., Wayne D. Hoyer, and Leigh McAlister (1998), "Consumers' Perceptions of the Assortment Offered in a Grocery Category: The Impact of Item Reduction," *Journal of Marketing Research*, 35 (May), 166–76.

Bruno, Hernan and Naufel Vilcassim (forthcoming), "Structural Demand Estimation with Varying Levels of Availability", *Marketing Science.*

Campo, Katia, Els Gijsbrechts, Patricia Nisol (2003), "The Impact of Retailer Stockouts on Whether, How Much, and What to Buy", *International Journal of Research in Marketing,* 20, 3, 273-286.

Che, Hai, K. Sudhir and P.B. Seetharaman (2007), "Bounded Rationality in Pricing Under State Dependent Demand: Do Firms Look Ahead? How Far Ahead?" *Journal of Marketing Research* 44, 3, 434-449

Chintagunta, Pradeep K., Dipak Jain, Naufel J. Vilcassim (1991), "Investigating heterogeneity in brand preferences in logit models for panel data." *Journal of Marketing Research,* 28, 417–428.

Erdem, Tulin, Susumu Imai, and Michael Keane (2003), "Brand and Quantity Choice Dynamics under Price Uncertainty," *Quantitative Marketing and Economics*, 1,1, 5-64.

Fader, Peter S. and Bruce G.S. Hardie (1996), "Modeling Consumer Choice Among SKUs," *Journal of Marketing Research*, 33(November), 442-452.

Fitzsimons, Gavan J. (2000), "Consumer response to stockouts," *Journal of Consumer Research*, 27, 249-266.

Gonül, Fusun and Kanan Srinivasan (1993) "Modeling Multiple Sources of Heterogeneity in Multinomial Logit Models," *Marketing Science*, 12, 213-29.

Gruen, Thomas W., Daniel Corsten and Sundrr Bharadwaj (2002). *Retail Out of Stocks: A Worldwide Examination of Causes, Rates, and Consumer Responses.* Washington D.C.: Grocery Manufacturers of America.

Gupta, Sachin, Anil Kaul, and Dick R. Wittink (1996), "Do Household Scanner Panel

Data Provide Representative Inferences from Brand Choices: A Comparison with Store Data," *Journal of Marketing Research*, 33 (November), 383-99.

Hauser, John R. and Birger Wernerfelt (1990), "An Evaluation Cost Model of Consideration Sets," *Journal of Consumer Research*, 16, (March), 393-408.

Kalyanam, Kirthi, Sharad Borle, and Peter Boatwright (2007), “Deconstructing Each Item’s Category Contribution,” *Marketing Science*, 26, 327-341.

Lynn, Michael (1991), “Scarcity Effects on Value: A Quantitative Review of the commodity Theory Literature,” *Psychology & Marketing*, 8(1), 43-57

Musalem, Andrés, Marcelo Olivares, Eric T. Bradlow, Christian Terwiesch, and Daniel Corsten (2008), “Structural Estimation of the Effect of Out-of-Stocks,” working paper, Duke University.

Roberts, John H. and James M. Lattin (1991), Development and Testing of a Model of Consideration Set Composition, *Journal of Marketing Research*, 28, 429–440.

Seetharaman, P.B., Andrew Ainslie, and Pradeep Chintagunta (1999), “Investigating Household State Dependence Effects Across Categories,” *Journal of Marketing Research*, 36 (November), 488–500.

Zhang, Jie and Aradna Krishna (2007), “Customizing Promotions in Online Stores,” *Journal of Marketing Research*, 44 (November), 545–559.

TABLE 1: Summary of Price, Market Shares, and Out of Stock Observations

Brand	Price ($/oz)	Market Share	OOS Per Trip	Correlation between Shares and OOS/TRIP
Bacon				
Oscar Mayer	0.37	0.32	0.35	0.85
Butchers	0.20	0.16	0.11	
Hormel Black Label	0.36	0.14	0.26	
Store Brand	0.23	0.11	0.10	
Others	0.37	0.11	0.19	
Farmer John	0.23	0.10	0.05	
Tyson Bacon	0.36	0.03	0.04	
Jones	0.79	0.02	0.04	
Ketchup				
Heinz	0.09	0.72	0.24	0.98
Store Brand	0.07	0.27	0.11	
Del Monte	0.08	0.02	0.08	
Laundry Detergent				
Tide	0.06	0.56	1.46	0.97
All	0.04	0.18	0.83	
Cheer	0.07	0.09	0.26	
Store Brand	0.04	0.07	0.43	
Wisk	0.05	0.05	0.24	
Arm & Hammer	0.04	0.02	0.20	
Gain	0.05	0.02	0.15	
Orange Juice				
Tropicana	0.04	0.43	0.75	0.95
Minute Mate	0.04	0.43	1.15	
Florida	0.04	0.11	0.19	
Simply Orange	0.05	0.02	0.15	
Store Brand	0.03	0.01	0.05	
Organic	0.06	0.00	0.04	
Tissue				
Northern	0.52	0.38	0.91	0.99
Store Brand	0.40	0.33	0.77	
Charmin	0.63	0.11	0.24	
Kleenex	0.56	0.10	0.31	
Angel	0.26	0.04	0.19	
Scott	0.67	0.03	0.07	
Earth First	0.35	0.01	0.05	
Tuna				
Bumble Bee	0.24	0.42	0.58	0.73
Star-Kist	0.32	0.26	0.49	
Chicken Of Sea	0.21	0.19	0.26	
Store Brand	0.17	0.13	0.23	
Other	0.40	0.00	0.35	

TABLE 2: Summary Statistics of OOS and Price Promotion

	Total OOS Occasions of SKUs in the Estimation Sample	OOS Occasions under Price Promotion	% of OOS Occasions under Price Promotion	Average OOS SKUs' Price Cut / Regular Price (%)	Average OOS SKUs' Price Cut (in dollars)	Average Non-OOS SKUs' Price Cut / Regular Price (%)	Average Non-OOS SKUs' Price Cut (in dollars)
Bacon	624	368	58.97%	25.83%	-1.42	16.68%	-0.88
Ketchup	274	201	73.36%	24.75%	-0.79	11.90%	-0.37
Laundry Detergent	2411	1595	66.16%	23.04%	-2.03	19.35%	-1.70
Orange Juice	2547	2272	89.20%	37.91%	-2.05	25.17%	-1.30
Tissue	1370	821	59.93%	19.19%	-1.45	10.32%	-0.75
Tuna	459	302	65.80%	28.94%	-0.56	11.67%	-0.21

TABLE 3: Summary of Demographics

	Number of Households	Income	Household Size	Children	Distance
Bacon	174	130.60	0.38	0.26	1.92
Ketchup	110	127.10	0.35	0.24	3.50
Laundry Detergent	109	196.00	0.32	0.20	2.01
Orange Juice	171	187.40	0.31	0.22	1.70
Tissue	174	127.80	0.33	0.16	1.95
Tuna	215	124.10	0.29	0.16	3.22

Income (thousand dollars): annual household income.
Household Size: a dummy variable that equals to 1 if the household size is greater or equal to 3
Children: a dummy variable that equals to 1 if there is (are) a child (children) in a family.
Distance (miles): distance to the store.

TABLE 4: Summary of Out-of-Stock Data

	Total OOS occasions of SKUs in Estimation Sample	Average OOS time recorded in the category	Average time (hours) between OOS time and last purchase	Average time (hours) between OOS time and next purchase
Bacon	624	6:18PM	8.16	15.38
Ketchup	274	5:40PM	10.32	18.50
Laundry Detergent	2411	5:36PM	10.80	15.63
Orange Juice	2547	6:35PM	7.44	12.22
Tissue	1370	6:10PM	5.04	12.80
Tuna	459	6:40PM	14.16	14.90

TABLE 5: Fit Statistics for Model Comparisons

		LL	AIC	BIC	# param.
Bacon	Model 1	-19867.3	39824.6	40102.4	36
	Model 2	-19704.8	39481.6	39759.4	36
	Model 3	-19689.9	39441.8	39750.5	40
Ketchup	Model 1	-8036.2	16112.4	16175.6	20
	Model 2	-7979.7	15999.4	16062.6	20
	Model 3	-7969.4	15986.8	16062.6	24
Laundry Detergent	Model 1	-4615.5	9315.0	9428.0	42
	Model 2	-4423.2	8930.4	9043.4	42
	Model 3	-4403.3	8898.6	9022.4	46
Orange Juice	Model 1	-16448.2	32950.4	33035.2	27
	Model 2	-16352.8	32759.6	32844.4	27
	Model 3	-16341.4	32743.8	32842.2	31
Tissue	Model 1	-14213.1	28482.2	28570.7	28
	Model 2	-13794.0	27644.0	27732.5	28
	Model 3	-13735.9	27535.8	27636.9	32
Tuna	Model 1	-15155.9	30373.8	30478.3	31
	Model 2	-15010.0	30082.0	30186.5	31
	Model 3	-14992.1	30054.2	30172.2	35

TABLE 6: Price Coefficient Estimates from Models with and without OOS effects

Price Coefficient				
	Model 1	Model 2	Model 3	Difference between Model 1 and 3 (%)
Bacon	-2.59	-2.82	-2.92	13.2%
	(0.27)	(0.32)	(0.25)	
Ketchup	-17.31	-18.04	-18.27	5.6%
	(1.17)	(1.00)	(1.35)	
Laundry Detergent	-94.65	-98.09	-99.19	4.8%
	(2.69)	(3.07)	(2.91)	
Orange Juice	-158.84	-159.93	-161.75	1.8%
	(1.11)	(1.02)	(1.36)	
Tissue	-4.21	-4.95	-5.01	19.0%
	(0.21)	(0.22)	(0.22)	
Tuna	-7.11	-7.22	-7.23	1.7%
	(0.21)	(0.47)	(0.22)	
Category Price Elasticity				
Bacon	-0.87	-0.93	-0.93	6.9%
Ketchup	-1.33	-1.39	-1.38	3.8%
Laundry Detergent	-3.67	-3.72	-3.73	1.7%
Orange Juice	-4.50	-4.53	-4.57	1.6%
Tissue	-2.17	-2.41	-2.42	11.5%
Tuna	-1.00	-1.02	-1.03	3.0%

TABLE 7: Effects of Out of Stock on SKU Preference

	Inter-temporal Effect (γ_1)	Contextual Effect (γ_2)	Average Inter-purchase Time (Days)	Herfindahl Index
Bacon	0.11	-0.79	24.10	0.15
	(0.09)	(0.12)		
Ketchup	0.12	3.75	66.13	0.51
	(0.16)	(1.38)		
Laundry Detergent	0.14	-3.52	49.52	0.18
	(0.14)	(1.16)		
Orange Juice	-0.31	-1.33	15.27	0.15
	(0.15)	(0.43)		
Tissue	0.25	-1.66	33.97	0.22
	(0.16)	(0.58)		
Tuna	-0.02	2.66	31.02	0.30
	(0.01)	(0.68)		

TABLE 8: The Relationship Between Household Level Purchase Patterns to and OOS Effects at Household Level

Dependent Variable	$\hat{\gamma}_{2h}$		$\hat{\gamma}_{1h}$	
Independent Variable	Herfindahl Index at Household level		Inter-purchase Time at Household Level	
	Estimates	Std Err	Estimates	Std Err
Bacon	0.09	0.04	0.07	0.02
Ketchup	0.58	0.18	0.03	0.00
Laundry Detergent	0.97	0.44	0.03	0.00
Orange Juice	0.31	0.70	0.06	0.02
Tissue	0.13	0.06	0.04	0.01
Tuna	0.09	0.03	0.04	0.01

TABLE 9: Counterfactual Analysis: Effects of OOS on Brand Choice Probabilities

	Average OOS Elasticity	γ_1,γ_2 (1)	$\gamma_1, \gamma_2=0$ (2)	$\gamma_1=0, \gamma_2=0$ (3)	Effect of γ_2 (4)*	Effect of γ_1 (5)**
Bacon	own	-0.10	-0.10	-0.11		16.65%
	cross	0.01	0.01	0.01	-19.96%	
Ketchup	own	-0.08	-0.08	-0.17		104.24%
	cross	0.02	0.01	0.02	35.21%	
Laundry Detergent	own	-0.12	-0.12	-0.13		7.04%
	cross	0.01	0.02	0.02	-25.23%	
Orange Juice	own	-0.11	-0.11	-0.10		-15.72%
	cross	0.02	0.02	0.01	-12.98%	
Tissue	Own	-0.08	-0.08	-0.11		37.84%
	cross	0.00	0.01	0.01	-12.39%	
Tuna	Own	-0.14	-0.13	-0.13		-4.13%
	cross	0.01	0.01	0.01	30.54%	

*: Effect of γ_2 is calculated as: [(1)-(2)] divided by the absolute value of (1)
**: Effect of γ_1 is calculated as: [(2)-(3)] divided by the absolute value of (1)

TABLE 10: Counterfactual Analysis : Category Revenue Change with OOS Eliminated

(1) γ_1,γ_2			
Category	With OOS	Without OOS	Change by Eliminating OOS (%)
Bacon	27303	27848	1.96%
Ketchup	5163	5142	-0.41%
Laundry Detergent	9808	10411	5.79%
Orange Juice	21034	21120	0.41%
Tissue	22202	23824	6.81%
Tuna	15955	16244	1.78%
(2) γ_1, γ_2=0			
Category	With OOS	Without OOS	Change by Eliminating OOS (%)
Bacon	27402	27848	1.60%
Ketchup	5134	5142	0.16%
Laundry Detergent	10097	10411	3.02%
Orange Juice	21105	21120	0.07%
Tissue	22796	23824	8.51%
Tuna	15605	16244	3.93%
(3) γ_1=0, γ_2=0			
Category	With OOS	Without OOS	Change by Eliminating OOS (%)
Bacon	27276	27848	2.05%
Ketchup	5083	5142	1.15%
Laundry Detergent	10011	10411	3.84%
Orange Juice	21194	21120	-0.35%
Tissue	21031	23824	11.72%
Tuna	15659	16244	3.60%

FIGURE 1: Counterfactual Analysis: The Relationship between a Brand's Marketing Share and the Impact of Its OOS on Category Sales

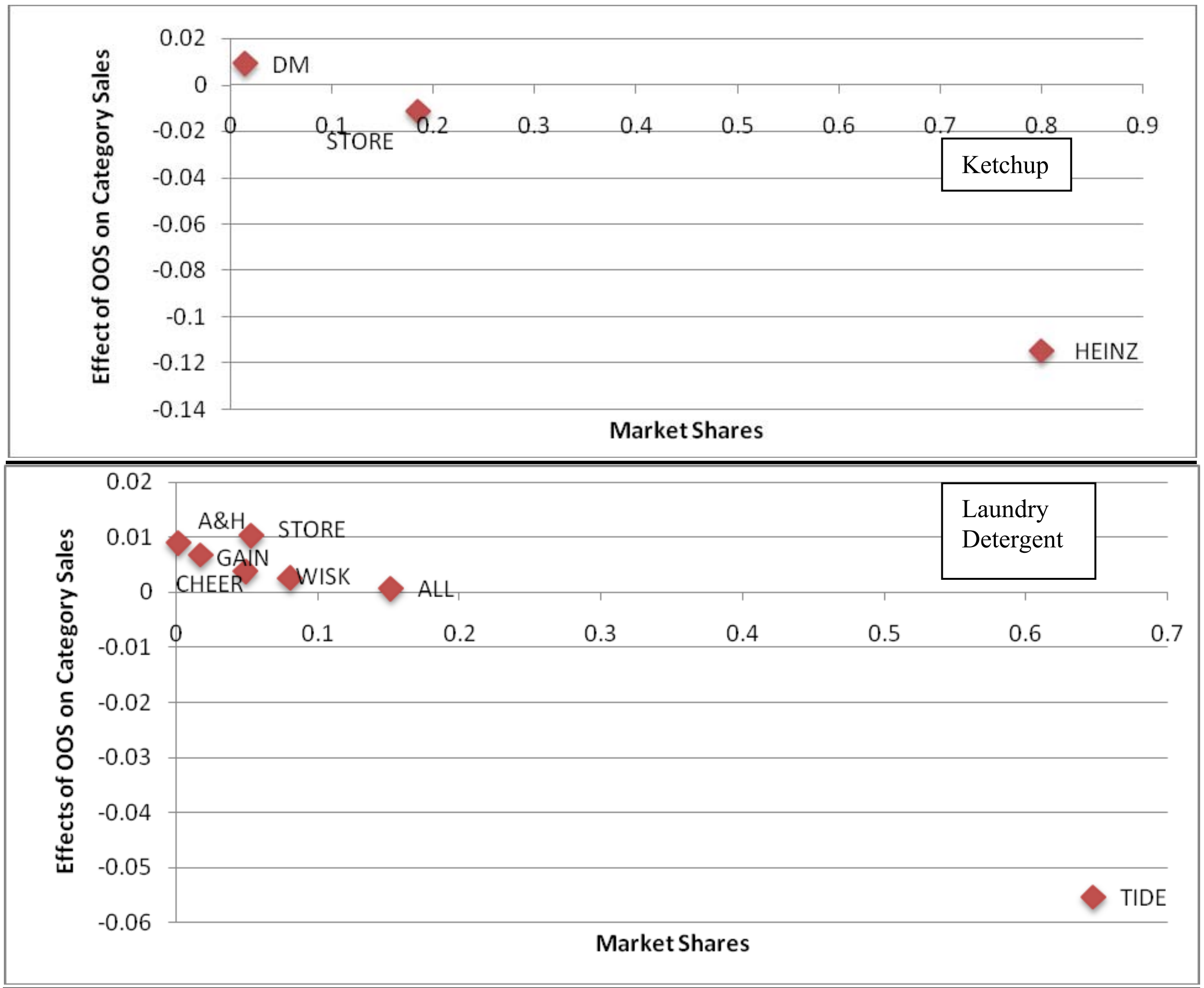

FIGURE 1: Counterfactual Analysis: The Relationship between a Brand's Marketing Share and the Impact of Its OOS on Category Sales (Continued)

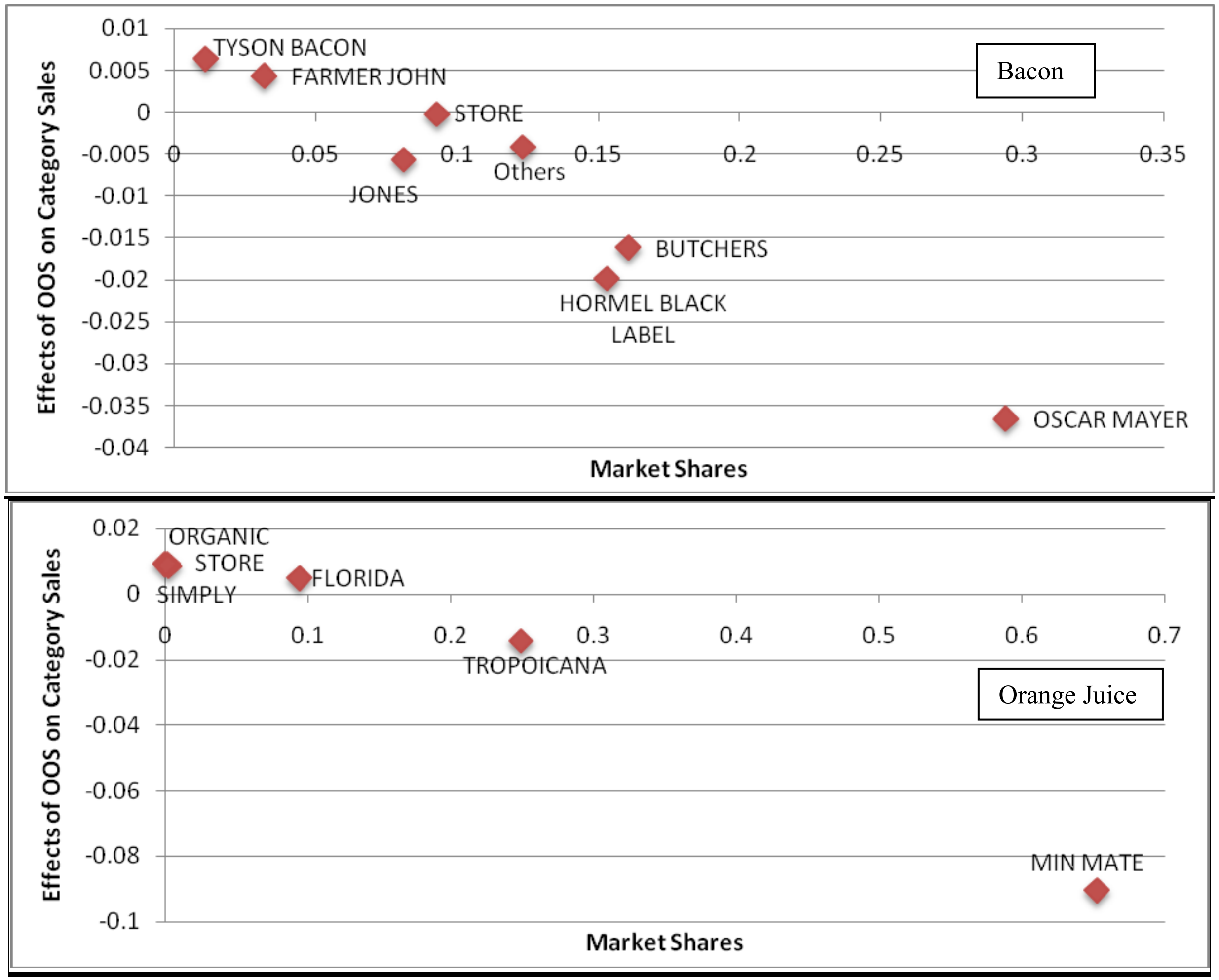

FIGURE 1: Counterfactual Analysis: The Relationship between a Brand's Marketing Share and the Impact of Its OOS on Category Sales (Continued)