The Impact of Disclosing Inventory-Scarcity Messages on Purchase Frequencies and Daily Sales in Online Retailing

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To influence consumer demand, some online retailers post messages (e.g., “5 units or less left in stock”) on their product webpages to signal impending stockouts. These “scarcity” messages provide consumers “partial” inventory information, revealing only an upper bound on the number of units available for sale. To examine the impact of these messages, we scraped price and sales data from the website of an online retailer across hundreds of durable consumer goods “before” and “after” the retailer posted these messages and during multiple inventory replenishment cycles. We then used these data to assess empirically the effect of these messages on purchase frequencies and daily sales of individual products. We find that posting these messages can increase purchase frequencies by an average of 14.80%. However, this effect is contingent on items that move slowly in relation to other products in the assortment. We also observe that the disclosure of these scarcity messages can decrease daily sales by an average of 17.60% and that this effect is most pronounced for products that consumers purchase in large quantities. This result suggests that the inventory information in these messages has a negative influence on the sales prospects of durable goods.

Keywords: *Operations management-marketing interface, inventory management, online retailing, econometrics.*

1. Introduction

Low search costs on the Internet enable consumers to compare many retail offers freely which, in turn, exacerbates certain purchasing behaviors, including the active pursuit of bargains (Brynjolfsson and Smith, 2000; Zhang et al., 2006) and the postponement of purchases in anticipation of future price drops and higher inventory availability (Aviv et al., 2009 and Netessine and Tang, 2009). To counteract these behaviors, some retailers offer “flash sales” of deeply discounted items for limited times (usually 24 hours), during which inventory availability information is available to stimulate consumers to commit to their purchases (Ferreira et al., 2016). At Amazon, for instance, flash sales provide shoppers with continuous real-time information about inventory availability for each stock-keeping unit (SKU) throughout the entire duration of each sales event.

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According to studies by Cui et al. (2018) and Wagner et al. (2018) a decrease in inventory availability during these events can increase the frequency in which consumers purchase the deals.

Many retailers, however, are apprehensive about disclosing "exact" inventory information to the public because they fear that this information may give their competitors and suppliers sensitive insights into their inventory management and pricing policies (Fisher et al., 2017). Furthermore, in some cases, retailers actually lack real-time inventory information to share with the public. This may help explain why retailers, such as Walmart, have chosen in the past to disclose only *"partial"* inventory information contained in messages alerting consumers about the *maximum* number of units available in stock when the actual inventory level drops below this upper bound. For instance, by posting a message alerting shoppers that an SKU has "5 units or less left in stock" when inventory drops below this threshold, a retailer can let consumers know of the maximum amount of inventory available for sale. Since these "scarcity messages" contain only partial inventory information, consumers do not know the *exact* inventory levels available for sale at any point before purchase.

The use of these messages has not been limited to flash sales settings. Retailers, such as Overstock, have used them in mainstream online environments in which products are available for sale over indefinite time horizons and multiple inventory replenishment cycles. The selling strategies in these environments differ notably from those in flash sales settings, where retailers typically promote heavily discounted items in limited quantities (i.e., with no inventory replenishments) and for extremely short durations to attract bargain hunters who are inherently interested in taking advantage of these temporary promotions. Consequently, these consumers will be more likely to purchase when they observe that inventory is running low (Sodero and Rabinovich, 2017). Because of these unique selling strategies associated with flash sales, the results by Cui et al. (2018) and Wagner et al. (2018) may not hold in mainstream settings, where consumers often make purchasing decisions based on their personal needs, as opposed to opportunistically, upon encountering discounted offers available during short periods of time.

To our knowledge, no research has evaluated the impact that the disclosure of scarcity messages has on durable consumer goods' sales in mainstream online retail environments. Our objective is to address this research gap. We are only aware of a study by Sodero et al. (2017) that also focused on these environments. However, this research centered on the relationship between purchasing frequencies and reductions in inventory-level information displayed continuously to consumers at all times. As a result, Sodero et al. (2017) were unable to estimate the impact of the *initial disclosure* of scarcity information on sales because they had no way of comparing sales "before" versus "after" consumers' exposure to this information. We address this research gap by evaluating differences in sales "before" versus "after" a retailer posts scarcity messages informing consumers about maximum inventory amounts available for sale for its products. Because the information in this type of messages is much simpler to obtain for online retailers, and it is less competitively risky for retailers to share with the public, its disclosure has significant applicability as a mechanism to influence consumers' purchasing behavior. Hence, addressing this research gap is not only relevant academically, but also significant for a wide segment of practitioners in the retail industry.

Furthermore, the study by Sodero et al (2017), as well as the research by Cui et al. (2018) and Wagner et al. (2018), focused their evaluation on consumer purchases limited to only *one unit per SKU*. In our research, purchases are not limited to any amount, making the results we obtain more relevant for mainstream markets in which retailers sell consumer goods for which purchase quantities are unconstrained. Moreover, by considering a setting where quantities purchased by consumers are not limited to only one unit, we can differentiate the impact of inventory messages' disclosure on the *frequency of purchase* (based on *inter-purchase times* measured in days) versus its impact on total *daily sales* quantities for each SKU. Thus, we measure the effects of posting scarcity messages not only based on each SKU's purchase frequency—as Sodero et al (2017), Cui et al. (2018), and Wagner et al. (2018) did so in the past—but also based on each SKU's daily sales.

To perform this evaluation, we collected data (prices, time of transactions, daily sales amounts, etc.) from a focal retailer who posted scarcity messages with partial inventory availability information ("5 or less left in stock") every time the inventory level of an SKU dropped below six units. Because this retailer sells durable consumer goods available for purchase with no time or inventory cycle restrictions and no purchase quantity constraints, we can examine the impact of the posting of these messages on both the frequency of purchase and the daily sales for each SKU over extended time periods. In so doing, we can partial out time effects from the effects of inventory messages' disclosure on sales in our analysis. Controlling for these time effects has not been possible in prior research. Cui et al. (2018) and Wagner et al. (2018), for instance, could not account for these effects because all flash sales events in their study were of short duration *and* involved no inventory replenishments. Therefore, the effects that they observed on sales caused by reductions in inventory levels may vary in cases where inventories are available for sale over longer periods or over multiple inventory cycles.

Moreover, because our focal retailer sells different SKUs without imposing any purchase quantity limits, we are able to isolate the effect that the disclosure of its scarcity messages has on sales from the *censoring effects* that reductions in inventory levels have on sales, which are independent of scarcity messages' disclosures. Furthermore, having no limitations imposed by the retailer on purchase quantities by consumers allows us to take advantage of *heterogeneity in sales* among the retailer's SKUs to inform on differences in the effects that the disclosure of scarcity messages has on purchase frequencies and daily sales for products that sell at different rates (i.e., fast moving versus slow moving products) and in large versus small daily sales amounts. Finally, because prices in our data vary across products and over time, our analysis can also isolate the effect of *price variations* on purchase frequencies and daily sales. To our knowledge, no paper has examined these effects as part of an evaluation of the impact on sales by the initial disclosure of inventory information to consumers online. This examination carries important implications about the effectiveness of inventory messages in reducing inventory costs for retailers.

Consistent with expectations that the disclosure of scarcity messages signaling low inventory availability can induce consumers to buy without delay, we find that the posting of these messages can *reduce* the average inter-purchase time by 14.80%. However, this effect is limited to items that move slowly in relation to other products. Specifically, SKUs in the bottom 51% of the sample's distribution of purchasing frequency will benefit from the disclosure of these messages in terms of inter-purchase time.

We also observe that the posting of these scarcity messages can *reduce* daily sales by an average of 17.60%. This is consistent with research by Wolfe (1968) and Koschat (2008), among others. These authors showed that when consumers make buying decisions for products based on demand needs, instead of opportunistically based on the availability of deep but short-lived discounts, low inventory levels will influence adversely their inferences regarding the products' quality in relation to other items that are available for sale currently or may become available for sale in the future. According to our results, this adverse effect on daily sales is significantly more prominent among SKUs that are sold, on average, in larger daily amounts and over longer inter-purchase intervals. Thus, the negative effect that scarcity messages have on daily sales has a disproportionate impact on items that tend to sell in large order quantities.

2. Literature Review

Our paper is positioned broadly along with other research at the interface between the Operations Management (OM) and Marketing literatures that has studied a variety of phenomena in Internet environments (e.g., Rao et al., 2014; Rosenzweig et al., 2011; Boyer et al., 2002). Specifically, as discussed in Section 1, our study complements prior research by Cui et al. (2018), Wagner et al. (2018), and Sodero et al. (2017) that examined the effects of inventory levels on sales in online retail settings. In addition to this work, there is a relevant stream of studies that has examined empirically the impact of inventory displays on sales in offline settings. In general, these studies have evaluated how perceptions of inventory abundance influence shoppers' purchasing decisions. To evaluate this phenomenon empirically, these studies have had to tackle a variety of endogeneity concerns (particularly those involving sales, inventory levels, and pricing) that exist in traditional, brick and mortar environments. In the fashion industry, Wolfe (1968) and Boada-Collado and Martinez-de-Albeniz (2017) examined the impact of inventory levels on sales across items offered at different retail stores and found that inventory levels have a positive effect on sales. Koschat (2008) observed a similar effect on the sale of magazines at retail stores. Focusing on the automotive industry, Cachon et al. (2018) showed that scarcity at auto dealers can increase sales but this effect vanishes as variety increases.

Akin to these studies, we are interested in the sale of durable goods that consumers may purchase without time limitations. In so doing, we also contribute to an additional stream of literature in OM that has analyzed how sellers can benefit from disclosing opaque inventory information for this type of goods. As part of these strategies, sellers may only disclose information about the availability of a product but not the availability of that product's variants. For instance, a seller may reveal the exact amount of inventory available for a set of cloth napkins but not the exact amount available for specific colors. Through this strategy, sellers can discriminate among consumers who are sensitive about the availability of inventory for each of the product's variants versus those who are not. Jerath et al. (2010) observed that this strategy discourages consumers from waiting to purchase. More recently, Cui and Shin (2017) showed that when a seller offers multiple variants of the same product and the specific variant preferred by consumers is likely to stock out, the seller should disclose aggregate inventory levels across the variants to increase sales.

The type of inventory information disclosure that we consider in our paper can be interpreted as a variation of the type of opaque information examined by Jerath et al. (2010) and Cui and Shin (2017). In our case, the timing of the release of the scarcity message that the seller provides to consumers and the contents of this message ("5 or less left in stock") are uniform across products and remain unchanged over time. That is, the retailer releases the same message when stock levels fall below six units, regardless of the SKU. Moreover, the message's content does not change as a function of the actual amount of inventory available (5, 4, 3, 2 or 1 units) for an SKU. Thus, after the retailer posts this message, consumers will know that the upper bound of the inventory level is 5 units. On the other hand, before this message is displayed, consumers will know that there are at least 6 units available for sale; however, this is of little use for consumers since they will not know the extent to which the actual inventory level is above 6 (i.e., the actual inventory level can be 7 or 7,000 units). Essentially, by posting these scarcity messages, the retailer is effectively sharing with consumers inventory information with different levels of precision at different points in time. "After" the posting of a scarcity message, consumers will know there is a specific range in the inventory amounts available (from 1 to 5 units). However, "before" this message is disclosed, they will only know the minimum value in the range of inventory amounts available (i.e., 6 units).

3. Theoretical Framework

To understand the influence of inventory information on sales in an online environment, one must consider two effects initially identified by Koschat (2008) and Balakrishnan et al. (2004; 2008) in offline settings. The first effect, known as the "*Availability Effect,*" suggests that reductions in inventory will decrease the probability of a retailer being able to match the product amounts consumers wish to purchase. Therefore, as inventory decreases, the Availability Effect becomes stronger, regardless of the disclosure to consumers of any inventory information. This will lead to a reduction in purchase quantities and frequencies; hence lower daily sales.

The second effect reflects the *changes in a product's demand function* caused by consumers' exposure to inventory information; i.e., the maximum number of units available for sale in the scarcity message. As we shall explain in Section 3.1, this *"Demand Effect"* induces two countervailing forces that affect a product's purchasing frequency. Then, depending on the relative strength of these two forces, the Demand Effect can cause the product's daily sales to increase or decrease. We discuss Demand Effect's impact on daily sales in Section 3.2.

3.1. Demand Effect and Purchase Frequency

The Demand Effect may manifest itself in an *increase in the intensity of scarcity perceptions* among consumers after the retailer posts a scarcity message with information on an upper bound for a product's inventory. According to Commodity Theory (Brock 1968), product scarcity can create a "buying frenzy" among consumers who are particularly sensitive about possible stockouts (DeGraba, 1995) and have a positive utility from owning products that are not commonly available (Lynn, 1991). This implies that the disclosure of the upper bound information for products' inventory can "nudge" consumers to commit to their purchases earlier, which will shorten the SKUs' inter-purchase times.

On the other hand, scarcity messages can generate an opposite force that can *discourage* consumer purchases (Urban, 2005). Specifically, because scarcity messages inform consumers that stock levels are low, some consumers may infer that the retailer has chosen to forego replenishing its inventory because the products are undesirable, of low quality, or likely to become obsolete (Koschat, 2008). To the extent that low search costs on the Internet make it easy for consumers to look for other products elsewhere (Bakos, 1997), the disclosure of this inventory information may induce them to forego buying these items. Hence, the posting of scarcity messages can have a negative impact on purchase frequency, which will increase the length of the SKUs' inter-purchase times.

The juxtaposition of these opposite forces caused by the disclosure of scarcity messages with inventory upper bound information may result in one of two possible Demand Effect outcomes regarding time intervals between consumer purchases:

> *Hypothesis 1a (b).* The disclosure of scarcity messages with inventory upper bound information will shorten (lengthen) the time intervals between consumer purchases, i.e. inter-purchase times.

3.2. Demand Effect and Daily Sales

Daily sales for SKUs depend on their average order quantities and purchasing frequencies. The Demand Effect arising from the disclosure of upper bound information regarding products' inventory may yield a reduction in average purchase quantities, and thus daily sales, if the disclosure of this information deters consumers from making purchases in large quantities. However, daily sales will increase if the negative effect on daily sales caused by these decreases in purchase quantities is offset by a rise in the frequency of orders purchased by consumers to avoid stockouts following the disclosure of these scarcity messages. Thus, there also two possible outcomes for the retailer regarding the Demand Effect on daily sales caused by the disclosure of scarcity messages with inventory upper bound information:

> *Hypothesis 2a (b).* The disclosure of scarcity messages with inventory upper bound information will increase (decrease) daily sales.

4. Empirical Methodology

To conduct our empirical analyses and test the aforementioned hypotheses, we collected data from Bon-Ton (BT), a multi-channel retailer selling a variety of durable goods in the apparel, accessories, home furnishings, home appliances, and toy categories. Founded in 1898, BT sold products exclusively through catalogs and stores up until 2005, when it added its online channel. With annual net revenues of $2.7 billion in 2017 and 20% year over year growth in Internet sales (totaling almost $200 million annually by 2017), BT's online channel constituted a major source of revenue for the company.

We chose to use BT as a single focal retailer for our empirical analysis in order to hold constant various factors that could influence demand parameters independently of the Demand Effect caused by inventory scarcity messages. These factors include the retailer's brand (Chevalier and Goolsbee, 2003; Smith and Brynjolfsson, 2001), Web interface attributes (Olson and Boyer, 2003), and ordering, fulfillment, and product return options (Rao et al., 2011; Rabinovich et al., 2011). In this sense, our choice to focus on a single retailer for our empirical evaluation follows a similar logic behind a variety of studies that have used this approach to study a range of phenomena related to Internet operations (e.g., Olson et al., 2005).

In each of its SKUs' online displays, BT posts a scarcity message as soon as inventories available for sale fall below six units. Once stocks go below this threshold, BT displays a message on each product's page with limited inventory information letting consumers know that there are "5 [units] or less left in stock" for the SKU (please refer to Figure 1 for an example of this type of display). Although BT sells on its website products that are also available at its stores, we selected for our analysis products that were available for sale *exclusively* through the online channel, as advertised for each product on the retailer's website. In doing so, we wanted to ensure that the measurement of the Demand Effect in the online channel caused by the sharing of scarcity messages with online consumers was not biased by inventory availability at the store channel. Because BT offered all SKUs in its apparel category through the online and store channels, we did not include this category in our analysis. Also, note that although BT marketed exclusively online the SKUs we chose for our study, these items were available for sale through other retailers. Therefore, the SKUs' availability was not exclusive to BT.

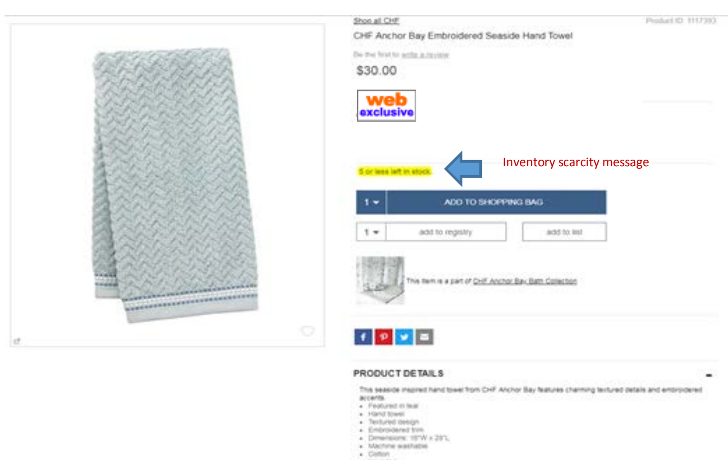

Figure 1 – Inventory scarcity message posted on BT website

4.1. Data Collection

We worked with all SKUs available for sale online across 28 different durable goods categories, including accessories, home furnishings, home appliances, and toy categories. For each SKU, we scraped pricing and inventory information BT posted online during a period of 18 months (from August 1, 2014 to January 31, 2016). Although BT posts the scarcity message ("5 or less left in stock") when the inventory of an SKU drops below 6 units and does not disclose on its product webpages information about the exact inventory level available for each SKU, it does maintain exact inventory level information in the source code for each of its SKUs' webpages. This enabled us to track the exact inventory level available for each SKU. We also tracked when BT posts its inventory scarcity message (i.e., "5 or less left in stock"). By recording the actual inventory level for each SKU, we could track when reductions in inventory levels occurred. From this information, we could then estimate when sales occurred and the amount of units sold for each SKU in order to compute the SKU's "inter-purchase times" and "daily sales."

In total, 199 SKUs had multiple replenishment cycles in which BT posted inventory scarcity messages during our 18-month time window. We focused on these 199 SKUs to conduct our study, in which we evaluate the effect on sales caused by BT's disclosure of inventory scarcity messages. Figure 2 shows the distribution of the number of SKUs across different product types in our data.

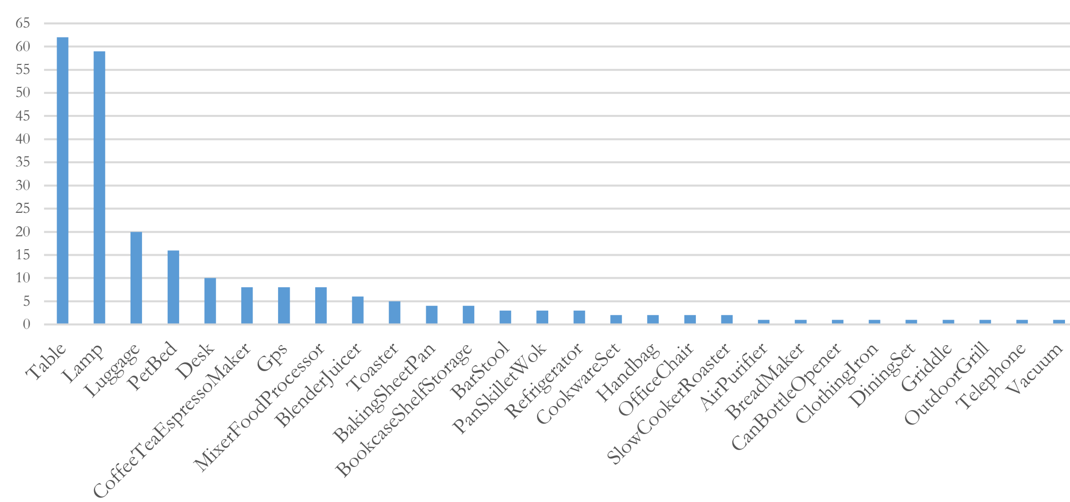

Figure 2 – Distribution of the number of SKUs across product types

We measured inter-purchase times and daily sales for each SKU in terms of the number of days since the previous sales transaction and the number of units sold per day, respectively. We used *days* as the unit of measurement for both of these variables because the SKUs in the sample include exclusively durable consumer goods, which are sold infrequently and are not subject to sharp rates of perishability. As we tracked and scraped inventory levels, we also monitored and recorded in parallel all changes in prices made by BT for each of the SKUs in the sample. We used this information to obtain each SKU price charged by BT over time, including the instances when sales took place. From our data, we found that, on average, BT changed the prices of the SKUs every 14.2 days (S.D. = 7.5 days). Therefore, the unit of measurement in days appears to be sufficiently granular relative to the frequency of changes in SKU prices.

Part A in the appendix offers additional details regarding our data and our methodology. These include a breakdown of the distribution of the number of purchases and inter-purchase times observed across purchase quantities as well as a variety of checks we conducted to test the robustness of the data collection methodology to produce non-biased measurements for inter-purchase times and daily sales. Note that to generate these measurements, we took into account the fact that the SKUs in our sample were not constantly available for sale during the 18-month sample period. BT introduced 183 SKUs to its assortment after the start of this period and removed 180 SKUs before the end of the period. On average, these SKUs were available for 142 days during the 18-month sample period. Moreover, there were days during this period when inventory for different SKUs decreased down to zero, making it impossible for consumers to purchase these products during these days. Consequently, to prevent biases in our measures of inter-purchase time and daily sales, we removed from consideration a total of 1,634 SKU-day observations when these out-of-stocks occurred.

Ultimately, the measurements of daily sales and inter-purchase time for each SKU excluded the "stockout" days between the dates of the sales that depleted the SKU's inventory and the dates of the SKU's restocking. Therefore, each SKU's daily sales measurements excluded all zero-unit "sales" observed during these "stockout" days. Moreover, the measurements of "inter-purchase time" leading up to the first sale after each inventory replenishment correspond to the number of days between the date when the replenishment occurred and the date of this sale.[1] Furthermore, our analyses used SKU fixed effects to control for any biases in our results caused by the late entry or early removal of SKUs from BT's assortment as well as to account for any other time-invariant effects inherent to each SKU that might have been unobservable to us. With this approach, we can identify the effect of scarcity disclosure using within-SKU variability in scarcity disclosure and generate results that are independent of any potential sampling bias.

4.2. Descriptive Statistics

Because the effects on sales caused by the disclosure of scarcity messages comprise two different outcomes, inter-purchase times and daily sales, we constructed two separate panels to estimate these effects from the data spanning all the SKUs in the sample. We use the first panel to investigate the impact of the disclosure of inventory messages on inter-purchase times and the second panel to estimate the effect of the disclosure of these messages on daily sales. Our choice to use separate panels to analyze these effects is consistent with the existence of the non-systematic relationship that exists between inter-purchase times and daily sales, as evidenced by the low correlation (-0.05) between both outcomes. Moreover, the use of separate panels allows us to obtain an amount of observations to evaluate the effects caused by the disclosure of inventory messages on daily sales that is not limited by the data collection for inter-purchase times.

Recall that we measured Inter-Purchase Time (*IPT*) as the time elapsed (in days) since the previous sales transaction for each SKU during the period of analysis. In those occasions when a transaction occurs on the same day as the one immediately before it, IPT equals zero. When the transaction occurs after a span of several days since the transaction preceding it, IPT corresponds to the number of days (i.e., the "time window") since the previous transaction. In all, we collected in the first panel 6,794 "IPT observations" over our 18-month sample window comprising all SKUs. Associated with each IPT observation, we also recorded whether a scarcity message was posted (at the start of the IPT window) informing consumers of a maximum amount of

[1] We thank the Associate Editor for this suggestion.

units in inventory remaining for an SKU (*Scarcity Message* = 1 or 0) and the values for the SKU's sales price (*Price*) and inventory level (*Inventory Level*). Table 1 provides the descriptive statistics of our data.

Variable	*Inter-purchase Time*	*Price*	*Scarcity Message*	*Inventory Level*
Inter-purchase Time (Days)	1			
Price (Dollars)	-0.018	1		
Scarcity Message (1= Yes, 0= No)	0.036	-0.061	1	
Inventory Level (Number of units)	-0.057	0.038	-0.231	1
Average	4.85	357.56	0.10	54.03
Standard Deviation	13.88	364.94	0.31	77.10
Minimum	0	14.99	0	0
Maximum	356	3,075	1	696
Number of Observations	6,794	6,794	6,794	6,794

Table 1 – Correlation Coefficients and Descriptive Statistics of Inter-Purchase Time Data

Observe from Table 1 that IPT's average is 4.85 days mainly because BT sells durable goods. Also, we notice that BT sells different types of durable goods so that some items are of low price (e.g., a can opener) while other items are of high price (e.g., a refrigerator). This is reflected in a wide range of prices among SKUs ($14.99 to $3,075). Finally, observe from Table 1 that the maximum value of IPT is 356. This may be an indication that BT sells some of the slow moving or "long tail" products exclusively through its online channel.

We used the second panel to estimate the effect that posting inventory messages has on daily sales. Associated with each SKU, the measurement for daily sales corresponds to the number of units sold (including zero units sold over "non-stockout" days) every day according to the selling price during that day. As shown in Table 2, we collect sales measurements for each SKU (Daily Sales) as part of each daily observation, along with the values for Price, Inventory Level, and Scarcity Message (defined above), over the 18-month period, resulting in 27,044 SKU-day observations. Note that because the second panel is based on 27,044 SKU-day observations and the first panel is based on 6,794 SKU-inter-purchase time observations, the descriptive statistics for Price, Scarcity Message, and Inventory Level reported in Table 2 are different from those reported in Table 1.

Variable	*Daily Sales*	*Price*	*Scarcity Message*	*Inventory Level*
Daily Sales (Number of units)	1			
Price (Dollars)	-0.014	1		
Scarcity Message (1= Yes, 0= No)	-0.063	-0.030	1	
Inventory Level (Number of units)	0.110	0.006	-0.370	1
Average	0.77	383.50	0.28	37.38
Standard Deviation	4.80	330.83	0.45	59.26
Minimum	0	19.99	0	0
Maximum	381	3,075	1	696
Number of Observations	27,044	27,044	27,044	27,044

Table 2 – Correlation Coefficients and Descriptive Statistics of Daily Sales Data

Among the statistics reported in Table 2, the average Daily Sales is 0.77 units with a standard deviation of 4.80. The magnitude of the standard deviation provides an indication of the variability that exists in daily sales across SKUs. Moreover, as in Table 1, the descriptive statistics for Price in Table 2 provide evidence of the existence of high variability in the values of the SKUs in the sample. Finally, Tables 1 and 2 report the values of the variables' Pearson correlation coefficients. We find that the highest correlation coefficient (in absolute value) is between Scarcity Message and Inventory Level (-0.231 in Table 1 and -0.370 in Table 2). Thus, our analysis using these variables is unlikely to be subject to multicollinearity problems.[2]

5. Statistical Models and Results

To estimate the Demand Effect of the disclosure of inventory messages on daily sales and inter-purchase times, we first used a "naïve" statistical modeling approach that makes no attempt to control for unobserved demand shocks that may make the disclosure of scarcity messages endogenous with respect to the dependent variables. We then used a "regression discontinuity design" (RDD) approach to address the issue of endogeneity as well as to allow for heterogeneity in the Demand Effects of scarcity messages as a function of differences in inherent sales patterns across SKUs.

5.1. Naïve modeling approach

Our initial analysis is based on the regression models as stated in Equations (1) and (2) below.

$$\ln(IPT_{it}+1)=\alpha_i+\sum_m \beta_m \cdot I(t\in m)+\gamma\cdot SM_{it}+\delta\cdot RP_{it}+\varepsilon_{it}, \tag{1}$$

$$\ln(Sales_{id}+1)=\alpha_i+\sum_m \beta_m \cdot I(d\in m)+\gamma\cdot SM_{id}+\delta\cdot \ln(P_{id})+\varepsilon_{id}. \tag{2}$$

In our models, we index SKU i = 1, …, 199 and we let t = 1,…, T_i denote different "purchase incidents" associated with SKU i in (1). We let the index d = 1, …, D_i denote different calendar days in (2). To capture the effect associated with different months m = 1,…, M (including seasonal effects), we introduce two indicator variables: (1) $I\ (t \in m)$ equals 1 if purchase incident t takes place in month m or 0, otherwise; and (2) $I\ (d \in m)$ equals 1 if the day of the sales d occurs in month m or 0, otherwise. IPT_{it} represents the time elapsed since the previous purchase occasion (measured in days) for SKU i. $Sales_{id}$ represents the sales (in units) of SKU i on day

[2] In the empirical analyses, we use log-transformed variables of sales and price. When we use these transformed variables, the correlation coefficients show marginal changes and the highest correlation coefficient is still -0.370.

d. Because the log of zero is undefined, we add a value of 1 to all IPT_{it} and $Sales_{id}$ values on the left hand side of Equations (1) and (2). On the right hand side of Equation (1), RP_{it} is a measure of price at t relative to price at t-1 (i.e., (the unit price of i at purchase instant t)/(the unit price of i at purchase instant t-1)). As IPT_{it} is the time between two consecutive purchase instants at t-1 and t, RP_{it} captures the change or trend in price preceding the purchase at t. [3] In Equation (2), P_{id} denotes the unit sales price of SKU i on day d.

Next, the variables SM_{it} and SM_{id} correspond to a scarcity message dummy variable. SM_{it} equals 1 if BT posted the scarcity message for SKU i between purchase instant $t-1$ and t. Otherwise, this variable equals 0. Similarly, SM_{id} equals 1 if BT had the scarcity message for SKU i on display at d. Otherwise, SM_{id} equals zero. Observe that the scarcity message dummy variable, SM, enables us to distinguish the purchasing behavior "before" and "after" BT posted its scarcity messages. Thus, the corresponding coefficient γ seeks to capture the Demand Effect as a function of the impact of scarcity messages on daily sales and inter-purchase times.

The term α_i captures "SKU-specific heterogeneity" in daily sales and inter-purchase time. Also, β_m captures the "month effect" in daily sales and inter-purchase time. In turn, ε_{it} and ε_{id} correspond to idiosyncratic random shock variables with mean zero. These variables capture unobserved factors influencing daily sales and inter-purchase time, respectively.

To estimate Equations (1) and (2), we first used a "fixed effect" dummy least square estimator. It is well known that this estimation approach is consistent and efficient. It also uses fewer assumptions compared to the random effect estimators approach (c.f., Chapter 10 in Wooldridge (2010)). Moreover, it is consistent under potential selection or endogeneity problems caused by correlations between α_i and the random shock variables ε_{it} and ε_{id}. In Equations (1) and (2), unobserved SKU-specific characteristics are captured by α_i. As

[3] Compared to a static measure of unit sale price at t (P_{it}), RP_{it} is a superior predictor of IPT_{it} because it takes into consideration the dynamic behavior of prices that led to the occurrence of the purchase at t and not earlier or later. Thus, although we estimated the models using unit sale price at t instead of RP_{it} and obtained results that are qualitatively consistent with those we present in the paper, the price effect in these models was insignificant.

we mentioned before, by estimating this parameter using a fixed effect approach in our regression model, we circumvent potential empirical problems due to selection or endogeneity issues.

Table 3 reports our estimation results of Equations (1) and (2). We omit the estimates of α_i's and β_m's to conserve space. Please note that we evaluate the robustness of these results in Part B in the appendix using alternative modeling forms and specifications in which we also make no attempt to control for unobserved demand shocks that may make the disclosure of scarcity messages endogenous with respect to the dependent variables[4]. The results from these alternative models are consistent with those presented in Table 3.

Fixed Effect Dummy Least Square						
Parameter	*Dependent Var.: ln(IPT+1)*			*Dependent Var.: ln(Sales+1)*		
	Estimate	*SE*	*t-val.*	*Estimate*	*SE*	*t-val.*
Relative Price *for IPT (δ)*	0.150***	0.032	4.657			
Price *for Sales (δ)*				-0.032**	0.014	-2.276
Scarcity Message *(γ)*	-0.075***	0.028	-2.682	-0.158***	0.009	-17.671
SKU Fixed Effect *(α_i)*		Yes			Yes	
Month Fixed Effect *(β_m)*		Yes			Yes	
F statistic		13.355***			24.360***	
R-squared		0.308			0.149	
Adj. R-squared		0.285			0.142	
Number of Obs.		6,794			27,044	

Clustered standard errors are used. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Table 3 – Baseline Estimation Results for Equations (1) and (2)

Observe from Table 3 that the estimated coefficient of *relative price* effects (δ) is significant and positive for inter-purchase time in Equation (1), and the estimated coefficient of *price* effects (δ) is negative and significant in daily sales in Equation (2). As expected, this result confirms that increases in price have overall detrimental effects on inter-purchase time and on daily sales, i.e., higher prices will lengthen inter-purchase time and reduce daily sales. Furthermore, the estimated coefficients of the scarcity message effect (γ) indicate that this message's disclosure has opposite effects on purchase frequencies and daily sales. On one hand, the scarcity message has a positive effect on purchase frequencies. This is because the estimated value for γ in Equation (1) is negative and significant (-0.075, $p<0.01$), indicating that, based on our logarithmic model specification, the

[4] Specifically, we considered the following alternative model specifications for the robustness checks: (1) linear models with unlogged dependent variables, (2) a Cox proportional hazard model, (3) a Poisson regression model, (3) a Negative binomial regression model, and (4) a Zero-inflated Negative binomial regression model.

inter-purchase time associated with sales transactions that occurred "after" BT posted the scarcity message is 7.5% *shorter* than that associated with sales transactions that occurred "before." On the other hand, the scarcity message has a negative and significant effect on daily sales. Based on the estimated γ coefficient in Equation (2) (γ =-0.158, $p<0.01$), daily sales are lower by 15.80% "after" BT posted the scarcity message than "before." Hence, these results support Hypotheses 1a and 2b.

5.2. RDD Modeling Approach

Because BT posts the inventory message ("5 or less left in stock") when stock for an SKU drops below 6 units, SM_{it} and SM_{id} can be correlated with *unobserved demand shocks*, which are included in the random shock variables ε_{it} and ε_{id}. This may generate endogeneity biases in our model estimation. The demand shocks resulting in the correlation between *SM* and ε can be decomposed into (a) time-invariant shocks (e.g. general popularity of an SKU, which does not vary over time) and (b) time-varying shocks (e.g. temporal popularity of a specific SKU due to seasonal needs or availability effects caused by variations in inventory levels over time). Time-invariant shocks can be handled by using a fixed effect approach. Specifically, this approach incorporates the time-invariant shocks into α_i and estimates α_i by treating them as model parameters. Note that we use a fixed effect approach in our model estimations and thus we circumvent this problem. A more challenging issue is the potential correlation between time-varying shocks and *SM*. We tackle this issue by using a "regression discontinuity design" (RDD) approach.

RDD is a quasi-experimental design approach that allows for the estimation of the causal effects of the intervention (the posting of a scarcity message in our case) using the discrete nature of the threshold of the intervention. RDD allows for an estimation of the causal effect when the treatment is assigned only at or below (or above) a cutoff value of a known variable. The literature refers to this variable as the "forcing variable." In our case, this variable corresponds to the inventory level and its cutoff value is 5 units, the threshold BT used to disclose its scarcity message. Since BT kept this threshold constant for all SKUs during our sampling period, the value of our key predictor, *SM*, changes abruptly at the threshold independently of time and SKU. Thus, time-varying shocks lying closely on either side of the threshold are comparable independently of the SKU. By using RDD, we exploit this condition to estimate *SM*'s causal effects on IPT_{it} and $Sales_{id}$ through a comparison of the values of these dependent variables on either side of the threshold (Angrist and Pischke, 2008).

Ho et al. (2017) provide a nice description of the RDD approach and they support RDD as a method to tackle endogeneity and make causal inferences in OM. Recently, a few scholars have used RDD to address research questions in operations and supply chain management. For instance, Coviello et al. (2018) used an RDD analysis to examine causal effects of increasing buyers' discretion in procurement outcomes for public projects. Anderson et al. (2012) exploited a sharp change in insurance coverage rates that results from young adults "aging out" of their parents' insurance plans and used RDD to estimate the effect of insurance coverage on the utilization of emergency and inpatient health care services.

Following Anderson et al (2012), we use a parametric linear spline estimator for our RDD analysis. Note that this approach is preferred to nonparametric methods, which are sensitive to bandwidth selection and require a large number of observations. Our RDD analysis is based on the following model specifications as stated in Equations (3) and (4).

$$\ln(IPT_{it}+1)=\alpha_i+\sum\nolimits_m \beta_m \cdot I(t\in m)+\gamma\cdot SM_{it}+\delta\cdot RP_{it}+\theta\cdot(Inv_{it}-\tau)+\rho\cdot(Inv_{it}-\tau)\cdot SM_{it}+\varepsilon_{it}, \qquad (3)$$

$$\ln(Sales_{id}+1)=\alpha_i+\sum\nolimits_m \beta_m \cdot I(d\in m)+\gamma\cdot SM_{id}+\delta\cdot \ln(P_{id})+\theta\cdot(Inv_{id}-\tau)+\rho\cdot(Inv_{id}-\tau)\cdot SM_{id}+\varepsilon_{id}, \qquad (4)$$

where Inv_{it} and Inv_{id} denote the inventory level for SKU *i* observed during purchase transaction *t* and on day *d*, respectively, and τ represents the pre-specified threshold value (i.e. 5 units). Note that SM_{it} (SM_{id}) equals 1 if $Inv_{it} \leq \tau$ ($Inv_{id} \leq \tau$) or zero; otherwise.

An advantage of using the RDD analysis is that we can disentangle the Demand Effect attributed to SM_{it} and SM_{id} from time-varying effects between Inv_{it} and IPT_{it} and Inv_{id} and $Sales_{id}$ induced by unobserved confounders, including temporal variations in SKUs' demand due to consumers' seasonal needs. In this case, while the parameter γ in Equations (3) and (4) measures the Demand Effect on IPT_{it} and $Sales_{id}$ by the disclosure of the scarcity message, the parameter θ captures the time-varying effects between Inv_{it} and IPT_{it} and between and Inv_{id} and $Sales_{id}$, induced by these unobserved confounders. Finally, note that Equations (3) and (4) allow

SM's causal effects on IPT_{it} and $Sales_{id}$ to vary with respect to Inv_{it} and Inv_{id} by including interaction terms between (Inv_{it} - τ) and SM_{it} and between ($Inv_{id} - \tau$) and SM_{id}. The value of the ρ coefficients estimated for these interaction terms will capture the magnitude of these variation effects, which can be attributed to unobserved variations in availability caused by changes in inventory levels once scarcity messages are disclosed.

Panel A in Table 4 reports the estimation results of Equations (3) and (4). The estimated coefficients of price effects are significantly positive in inter-purchase time ($\delta = 0.148$) and significantly negative in daily sales ($\delta = -0.03$). These results are consistent with those in Section 5.1. Moreover, the statistically significant values estimated for the coefficients of the *SM* dummies (γ) indicate that the disclosure of the scarcity message can contribute to shorten inter-purchase time and reduce daily sales. Specifically, once the scarcity message is disclosed, SKUs' inter-purchase time is shortened by 14.80%. In contrast, the disclosure of the scarcity message decreases daily sales for an SKU by 17.60%. Overall, the estimated values of these coefficients echo our findings using Equations (1) and (2) (as reported in Table 3) and provide further support for Hypotheses 1a and 2b. Note also that these results are consistent with those obtained using the same specification and RDD modeling form but excluding all SKUs with extended stockout observations to account for biases due to potentially unobserved heterogeneity in service levels across the products (please refer to Part C in the appendix).

The results in Panels B, C, and D in Table 4 also add robustness to our findings using alternative specifications within the RDD approach. First, we drop a control variable (Price) from the models (Panel B). We then use in Panel C an alternative dependent variable's specification, based on level (i.e., direct measurement) variables instead of log-transformed ones. Finally, in Panel D, we use the same alternative dependent variables specification as in Panel C and the same set of regressors in Panel B. The results from these alternative specifications are largely consistent with those in Panel A and with those in Table 3.

Only one difference in the values reported in Table 4 for the ρ coefficient in Equation (3) is worth discussing. Although Panels A through D report values for this coefficient that are negative, only the estimated values of ρ in Panels C and D are statistically different from zero. Based on the estimated values for ρ (~-0.89) and γ (~-4.25) reported in Panels C and D, we can conclude that scarcity disclosure will cause inter-purchase time to decrease by about 4.25 days. However, every unit decrease in inventory for an average SKU below the disclosure threshold will cause inter-purchase time to increase by approximately 0.89 days. Note, however, that the offsetting value (0.89 days per unit decrease in inventory) is not large enough to remove the effect caused by disclosure on inter-purchase time as inventory draws down from the threshold (5 units). Specifically, when the stock level for an SKU is at 5 units, the disclosure of the scarcity message will reduce inter-purchase time by an average of 4.25 days. Once inventory drops from 5 to 4 units, the average Demand Effect from continuing to share the scarcity message with consumers will decrease (in absolute terms) from 4.25 to 3.36 days (4.25 – 0.89) due to the ρ coefficient effect. As inventory continues to drop, the Demand Effect will change further until reaching a value of -0.69 when the last unit remains in stock. At that point, the Demand Effect due to the scarcity message will still contribute to reduce the time needed to sell that unit by an average of 0.69 days.

In sum, the consistency in the results obtained across the different RDD specifications in Table 4 as well as in the results in Table 3 provide support for Hypotheses 1a and 2b. These results point to significantly negative effects by the disclosure of scarcity messages on inter-purchase times and daily sales.

Panel A	*Dependent Var.:*			*Dependent Var.: ln(Sales+1)*		
Parameter	***Estimate***	***SE***	***t-val.***	***Estimate***	***SE***	***t-val.***
Relative Price *for IPT* (δ)	0.148***	0.032	4.598			
Price *for Sales* (δ)				-0.032**	0.014	-2.284
Scarcity Message (γ)	-0.148**	0.064	-2.324	-0.176***	0.016	-11.208
θ	0.001***	0.000	3.567	0.000	0.000	-1.471
ρ	-0.027	0.018	-1.480	-0.006	0.005	-1.057
SKU Fixed Effect (α_i)		Yes			Yes	
Month Fixed Effect (β_m)		Yes			Yes	
F statistic		13.320***			22.300***	
R-square		0.309			0.149	
Adj. R-square		0.286			0.142	
Number of Obs.		6,794			27,044	
Panel B	*Dependent Var.:*			*Dependent Var.: ln(Sales+1)*		
Parameter	***Estimate***	***SE***	***t-val.***	***Estimate***	***SE***	***t-val.***
Scarcity Message (γ)	-0.150**	0.064	-2.354	-0.176***	0.016	-11.174
θ	0.001***	0.000	3.635	0.000	0.000	-1.448
ρ	-0.028	0.018	-1.499	-0.006	0.005	-1.070
SKU Fixed Effect (α_i)		Yes			Yes	
Month Fixed Effect (β_m)		Yes			Yes	
F statistic		13.250***			23.070***	
R-square		0.307			0.149	
Adj. R-square		0.284			0.142	
Number of Obs.		6,794			27,044	
Panel C	*Dependent Var.: IPT*			*Dependent Var.: Sales*		
Parameter	***Estimate***	***SE***	***t-val.***	***Estimate***	***SE***	***t-val.***

***Relative Price** for IPT (δ)*	2.197***	0.666	3.299			
***Price** for Sales (δ)*				-0.247**	0.120	-2.051
Scarcity Message (γ)	-4.193***	1.317	-3.183	-0.513***	0.137	-3.753
θ	0.016***	0.003	4.849	-0.001	0.001	-1.519
ρ	-0.875**	0.380	-2.355	0.025	0.045	0.558
SKU Fixed Effect (α_i)	Yes			Yes		
Month Fixed Effect (β_m)	Yes			Yes		
F statistic	4.959***			7.978***		
R-square	0.143			0.057		
Adj. R-square	0.114			0.050		
Number of Obs.	6,794			27,044		
Panel D	***Dependent Var.: IPT***			***Dependent Var.: Sales***		
Parameter	***Estimate***	***SE***	***t-val.***	***Estimate***	***SE***	***t-val.***
Scarcity Message (γ)	-4.373***	1.320	-3.312	-0.509***	0.137	-3.722
θ	0.016***	0.003	4.898	-0.001	0.001	-1.499
ρ	-0.901**	0.380	-2.369	0.025	0.045	0.547
SKU Fixed Effect (α_i)	Yes			Yes		
Month Fixed Effect (β_m)	Yes			Yes		
F statistic	4.924***			7.995***		
R-square	0.141			0.057		
Adj. R-square	0.113			0.050		
Number of Obs.	6,794			27,044		

Clustered std. errors are used. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Table 4 – Estimation results using RDD

5.3. Heterogeneity Effects of Scarcity Message Disclosures

We conclude our analysis with an evaluation of variations in Demand Effects induced by the disclosure of scarcity messages across products based on their inherent purchase frequencies (as a function of inter-purchase time – fast moving versus slow moving) and daily sales (as a function of the amount of units sold per day – high versus low quantities). For this analysis, we chose to use the same regression discontinuity design discussed in Section 5.2 to account for potential correlations between *SM* and unobserved demand shocks included in the random shock variables ε_{it} and ε_{id} and to be able to disentangle and estimate the Demand Effect. We present the specifications for this design in Equations (5)-(8) followed by the estimation results.

Scarcity message effect varying with SKU average daily sales (AS_i):

$$\ln(IPT_{it}+1) = \alpha_i + \sum_m \beta_m \cdot I(t \in m) + \left(\gamma_0 + \gamma_S \cdot \ln(AS_i)\right) \cdot SM_{it}$$

$$+ \delta \cdot RP_{it} + \theta \cdot (Inv_{it} - \tau) + \rho \cdot (Inv_{it} - \tau) \cdot SM_{it} + \varepsilon_{it}, \quad (5)$$

$$\ln(Sales_{id}+1) = \alpha_i + \sum_m \beta_m \cdot I(d \in m) + \big(\gamma_0 + \gamma_S \cdot \ln(AS_i)\big) \cdot SM_{id}$$

$$+ \delta \cdot \ln(P_{id}) + \theta \cdot (Inv_{id} - \tau) + \rho \cdot (Inv_{id} - \tau) \cdot SM_{id} + \varepsilon_{id}, \qquad (6)$$

Scarcity message effect varying with SKU average purchase frequency (AI_i):

$$\ln(IPT_{it}+1) = \alpha_i + \sum_m \beta_m \cdot I(t \in m) + \big(\gamma_0 + \gamma_I \cdot \ln(AI_i)\big) \cdot SM_{it}$$

$$+ \delta \cdot RP_{it} + \theta \cdot (Inv_{it} - \tau) + \rho \cdot (Inv_{it} - \tau) \cdot SM_{it} + \varepsilon_{it}, \qquad (7)$$

$$\ln(Sales_{id}+1) = \alpha_i + \sum_m \beta_m \cdot I(d \in m) + \big(\gamma_0 + \gamma_I \cdot \ln(AI_i)\big) \cdot SM_{id}$$

$$+ \delta \cdot \ln(P_{id}) + \theta \cdot (Inv_{id} - \tau) + \rho \cdot (Inv_{id} - \tau) \cdot SM_{id} + \varepsilon_{id}, \qquad (8)$$

where AS_i denotes the average daily sales of SKU i and AI_i denotes the average inter-purchase time of SKU i. AS_i and AI_i represent, on average, how large the daily sales are for an SKU and how frequently the SKU is sold, respectively. It is possible that reductions in inter-purchase times caused by the disclosure of scarcity messages may be more moderate among SKUs purchased more often and in greater daily amounts (lower AI_i and higher AS_i). On the other hand, the negative effects on daily sales following scarcity messages' disclosure may be more pronounced among SKUs purchased in lower frequencies and greater daily amounts (higher AI_i and higher AS_i) since demand for these SKUs may be subject to positive biases induced by higher inventory levels.

Table 5 shows the correlation matrix and the descriptive statistics for $\ln(AS_i)$ and $\ln(AI_i)$. In Equations (5) through (8), we allow the effect of scarcity message to vary with the logged values of AS_i and AI_i. The results we present in this section are based on this specification. However, note that we also verified that these results were consistent with those obtained using similar specifications to those in Equations (1) and (2) and can provide those results upon request. Moreover, in Part D of the appendix, we present a supplementary set of results obtained from a robustness test using a specification with categorical values (high= 1 and low= 0) for $\ln(AS_i)$ and $\ln(AI_i)$ based on median splits. These results are consistent with those below.

Variable	$\ln(AS_i)$	$\ln(AI_i)$
$\ln(AS_i)$	1	
$\ln(AI_i)$	-0.25	1
Average	0.99	1.55

Standard Deviation	0.63	0.85

Table 5 –Correlation Coefficients and Descriptive Statistics of Average Daily Sales and Average Purchasing Frequency

Panel A in Table 6 reports the estimation results of Equations (5) and (6). These results are consistent with those in Section 5.2. According to the statistically significant value estimated for the γ_0 coefficient in Equation (5), the Demand Effect induced by the disclosure of scarcity messages decreases inter-purchase times by 15.50%. In Equation (6), the estimated values for the γ_0 and γ_S coefficients indicate that the Demand Effect induced by scarcity disclosures has a negative effect on SKUs' daily sales contingent on the SKUs' average number of units sold per day. As average daily sales increase, the Demand Effect will become increasingly more negative. For instance, if an SKU's average daily sales is 3.62 units (Table 5), its daily sales will decrease by 20.45% (= -0.159*ln(3.62)) due to the Demand Effect induced by the disclosure of scarcity messages.

Panel B in Table 6 reports the estimation results of Equations (7) and (8). The results for Equation (7) show that the effect of scarcity message disclosure on inter-purchase times is no longer statistically significant. The association of the *SM* predictor with this outcome variable, as measured by the γ_0 coefficient, changes when we add the ln(*AI*) • *SM* predictor. According to the estimated value for the γ_I coefficient (-0.096), the latter predictor has a negative and statistically significant effect (at the 5% level) on the outcome variable. This implies that the disclosure of scarcity messages has a negative effect on inter-purchase time that is contingent on how *infrequently* SKUs sell. That is, the disclosure of scarcity messages will have a negative effect on inter-purchase times that will be more discernible depending on how *slowly* SKUs in the retailer's assortment move. In the results for Equation (8), we also observe a similar phenomenon. According to the values estimated for the γ_0 and γ_I coefficients (γ_0 = 0.173 and γ_I = -0.135), the disclosure of scarcity messages has a negative effect on daily sales depending on how infrequently SKUs sell.

Panel C reports the results from an analysis based on the *simultaneous inclusion* of the two interaction terms, ln(*AS*) • *SM* and ln(*AI*) • *SM*, as predictors in the equations with daily sales and inter-purchase time as dependent variables. The results in Panel C for inter-purchase time as dependent variable are consistent with those for Equation (7) in Panel B. Together, they suggest that the disclosure of scarcity messages has a negative effect on inter-purchase time that is contingent on how infrequently SKUs sell. Based on the specific set of results in Panel C, the estimated value for γ_I (-0.102) indicates that a one percent increase in *AI* will amplify by 0.102% the negative impact by scarcity messages' disclosure on the SKU's purchasing frequency.

In turn, the results for daily sales as dependent variable in Panel C show that the disclosure of scarcity messages has a negative effect on daily sales contingent on the SKUs average frequency of sales and daily sales amounts. The influence on the scarcity disclosure effect by the SKUs' average purchasing frequencies and daily sales amounts is significant. For instance, a one percent increase in *AS* and *AI* will decrease daily sales by approximately 0.225% (-0.225 = -0.119 - 0.106) and this decrease will offset almost completely the positive effect on daily sales attributed to the scarcity disclosure effect (according to the 0.229 value estimated for the γ_0 coefficient). As we expand to include SKUs with higher average daily sales and longer average inter-purchase times, the negative effects attributed to γ_S and γ_I will supersede the effect attributed to γ_0. Also note that, according to the estimated value for the ρ coefficient (-0.018), the Demand Effect induced by the disclosure of scarcity messages will vary depending on the number of units remaining in inventory. Daily sales will increase by 1.8% for every single-unit decrease in inventory below the scarcity disclosure threshold.

Panel A	*Dependent Var.: ln(IPT+1)*			*Dependent Var.: ln(Sales+1)*		
Parameters	**Estimate**	**SE**	**t-val.**	**Estimate**	**SE**	**t-val.**
***Relative Price** for IPT (δ)*	0.148***	0.032	4.598			
***Price** for Sales (δ)*				-0.029**	0.014	-2.065
***Scarcity Message** (γ_0)*	-0.155**	0.071	-2.191	-0.031	0.021	-1.498
ln(*AS*) • *SM* (γ_S)	0.011	0.048	0.225	-0.159***	0.015	-10.513
θ	0.001***	0.000	3.570	-0.0003***	0.0001	-3.193
ρ	-0.026	-0.019	-1.424	-0.011**	0.005	-2.009
***SKU Fixed Effect** (α_i)*		Yes			Yes	
***Month Fixed Effect** (β_m)*		Yes			Yes	
F statistic		13.264***			23.512***	
R-square		0.309			0.152	
Adj. R-square		0.286			0.145	
Number of Obs.		6,794			27,044	
Panel B	**Dependent Var.: ln(IPT+1)**			**Dependent Var.: ln(Sales+1)**		
Parameters	**Estimate**	**SE**	**t-val.**	**Estimate**	**SE**	**t-val.**
***Relative Price** for IPT (δ)*	0.148***	0.032	4.588			
***Price** for Sales (δ)*				-0.032**	0.014	-2.324
***Scarcity Message** (γ_0)*	0.013	0.091	0.146	0.173***	0.028	6.293
ln(*AI*) • *SM* (γ_I)	-0.096**	0.039	-2.505	-0.135***	0.009	-15.439
θ	0.001***	0.000	3.773	-0.0002*	0.0001	-1.760
ρ	-0.026	0.018	-1.428	-0.016***	0.005	-2.990

SKU Fixed Effect *(α_i)*		Yes			Yes	
Month Fixed Effect *(β_m)*		Yes			Yes	
F statistic		13.305***			24.245***	
R-*square*		0.310			0.156	
Adj. R-*square*		0.287			0.150	
Number of Obs.		6,794			27,044	
Panel C	**Dependent Var.: ln(IPT+1)**			**Dependent Var.: ln(Sales+1)**		
Parameters	**Estimate**	**SE**	**t-val.**	**Estimate**	**SE**	**t-val.**
Relative Price *for IPT (δ)*	0.148***	0.032	4.587			
Price *for Sales (δ)*				-0.030**	0.014	-2.172
Scarcity Message *(γ_0)*	0.038	0.104	0.362	0.229***	0.029	7.985
ln(*AS*) • *SM* (γ_S)	-0.024	0.050	-0.482	-0.106***	0.016	-6.810
ln(*AI*) • *SM* (γ_I)	-0.102**	0.040	-2.541	-0.119***	0.009	-13.188
θ	0.001***	0.000	3.716	-0.0003***	0.0001	-2.870
ρ	-0.028	0.019	1.487	-0.018***	0.005	-3.397
SKU Fixed Effect *(α_i)*		Yes			Yes	
Month Fixed Effect *(β_m)*		Yes			Yes	
F statistic		13.24***			24.39***	
R-*square*		0.310			0.157	
Adj. R-*square*		0.287			0.151	
Number of Obs.		6,794			27,044	

Clustered standard errors are used. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Table 6 - Estimation Results using RDD Interaction Models

6. Sensitivity Analysis

The results in Table 6 provide evidence of a significant SKU-wide heterogeneity in the Demand Effect induced by the disclosure of scarcity messages. In this section, we exploit this heterogeneity to conduct sensitivity analyses regarding our results' support for Hypotheses 1a and 2b and identify boundary conditions for the Demand Effect across SKUs' average inter-purchase times and average daily sales (AI_i and AS_i, respectively).

6.1. Sensitivity analysis of Hypothesis 1a results

From the results in Panel C (Table 6) for inter-purchase time as dependent variable, we determined that only SKUs with AI_i values greater than 4.26 days $\left(e^{\frac{\delta*1.00}{\gamma_I}} = e^{\frac{0.148}{0.102}}\right)$ will experience increases in their frequency of purchase due to the disclosure of scarcity messages. To obtain this value, we let $ln(IPT_{it}+1) = 0$ and solve for AI_i in Equation (9), while controlling for SKU and time fixed effects. Note that as part of this estimation, we set to zero those coefficients in Equation (9) with values estimated to be non-statistically different from zero in Panel C. We also assumed no SKU price variations (i.e., RP_{it}= 1.00), and SKU inventory levels of one unit at the time of observation (i.e., Inv_{it}= 1 and thus Inv_{it} - τ= -4 and SM_{it}= 1). These RP_{it} and Inv_{it} values generate conservative estimates of AI_i's lower-bound value necessary for SKUs to be immune from the effects described in Hypothesis 1a. Lower RP_{it} values and higher Inv_{it} values will decrease this lower-bound, thereby increasing the percentage of sampled SKUs immune from the effects in Hypothesis 1a.

$$\ln(IPT_{it}+1) = \alpha_i + \sum_m \beta_m \cdot I(t \in m) + \left(\gamma_0 + \gamma_S \cdot \ln(AS_i) + \gamma_I \cdot \ln(AI_i)\right) \cdot SM_{it} + \\ + \delta \cdot RP_{it} + \theta \cdot (Inv_{it} - \tau) + \rho \cdot (Inv_{it} - \tau) \cdot SM_{it} + \varepsilon_{id}, \quad (9)$$

In total, approximately 51% of SKUs in the sample have AI_i values that exceed the 4.26 threshold. As we mentioned earlier, this threshold will decrease with reductions in SKU prices. A 10% decrease in price for an SKU, reflected in a 0.90 value for RP_{it}, will lower the AI_i threshold to 3.69 days $\left(e^{\frac{\delta * 0.90}{\gamma_I}} = e^{\frac{0.148*0.90}{0.102}}\right)$ on average. In our sample, about 59% of SKUs have AI_i values above this threshold. Thus, the positive effect of scarcity messages on SKUs' purchasing frequency (as measured by inter-purchase time) will have a broader applicability when used in tandem with price discounts. In this particular case, a 10% price discount expands the applicability of this effect to an additional 8% of SKUs in the sample. Further increases in discounts (up to 60%, the largest discount in our sample) will expand the applicability of this effect to all SKUs with AI_i values greater than or equal to 1.79 days $\left(e^{\frac{0.148*0.40}{0.102}}\right)$. These SKUs account for approximately 89% of the sample.

6.2. Sensitivity analysis of Hypothesis 2b results

For Hypothesis 2b's analysis, we use the results in Panel C in Table 6 for daily sales as dependent variable to estimate how low AI_i needs to be in relation to AS_i for an SKU to be immune from any adverse effects on daily sales caused by the disclosure of scarcity messages (per Hypothesis 2b). To that end, we solve for AI_i over different values of AS_i (starting at 0) in Equation (10), while setting to zero those coefficients in Equation (10) with values estimated to be non-statistically different from zero in Panel C and letting $\ln(Sales_{id}+1) = 0$, P_{id}= \$14.99 (the lowest price in the panel), and Inv_{id}= 1 (and thus $Inv_{id} - \tau$= -4 and SM_{id}= 1). The values chosen for P_{id} and Inv_{id} generate conservative estimates of how low AI_i values need to be in relation to AS_i values for SKUs to be immune from the effects described in Hypothesis 2b. As P_{id} or Inv_{id} increases, these AI_i values will decrease, thereby reducing the percentage of sampled SKUs immune from the effects in Hypothesis 2b.

$$\ln(Sales_{id}+1) = \alpha_i + \sum_m \beta_m \cdot I(d \in m) + \left(\gamma_0 + \gamma_S \cdot \ln(AS_i) + \gamma_I \cdot \ln(AI_i)\right) \cdot SM_{id} + \delta \cdot \ln(P_{id}) + \theta \cdot (Inv_{id} - \tau) + \rho \cdot (Inv_{id} - \tau) \cdot SM_{id} + \varepsilon_{id}, \quad (10)$$

Figure 3 shows our estimation of AI_i as a function of AS_i, after controlling for SKU and time fixed effects. From Figure 3, we can determine that all SKUs with combinations of AS_i and AI_i values below the estimated function will be immune to negative Demand Effects in their daily sales from the disclosure of scarcity messages. These SKUs account for approximately 21% of the sample. Note that these SKUs correspond to those with the lowest average purchase quantities in the retailer's assortment. SKUs with higher AS_i and AI_i values will exhibit higher average purchase quantities. Moreover, the SKUs are assumed to be of low value. For higher-value SKUs, the estimated function in Figure 3 will shift down, closer to AS_i and AI_i equal to 0.

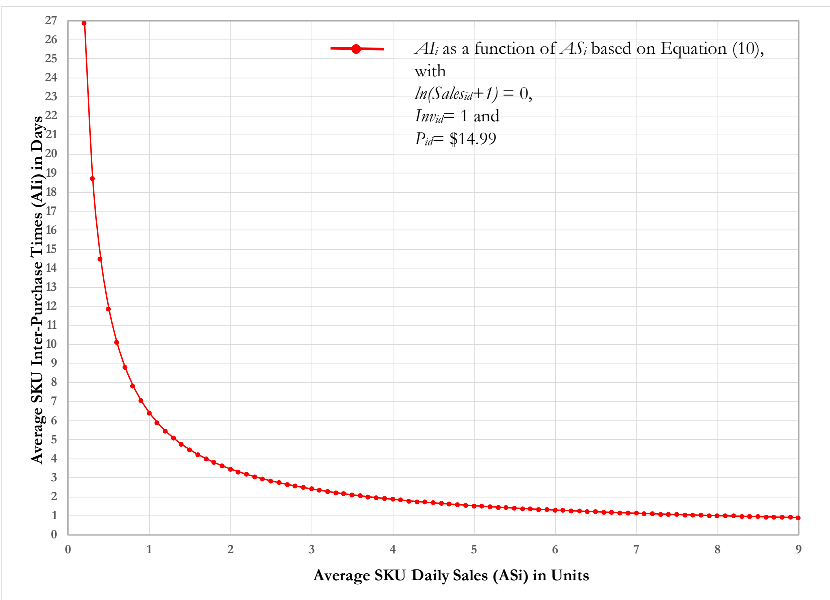

Figure 3 – Sensitivity Analysis of Hypothesis 2b Results as a Function of AS_i and AI_i

An additional consideration is that, regardless of the value of SKUs, discounts can further increase daily sales. According to our results, a reduction of 1% in SKU price will increase daily sales by 3%, on average (please refer to the value estimated for the price coefficient, $\delta = 0.03$, in Panel C in Table 6). Because this effect is independent of the disclosure of scarcity messages and of the SKUs' average purchase frequencies and daily sales, it carries greater weight in increasing daily sales for slow moving (high AI_i) SKUs, which are the items in the retailer's assortment exposed to the most severe negative effects by scarcity disclosure on daily sales.

Moreover, the price effect estimated in our analysis suggests that daily sales are highly price elastic – daily sales' price elasticity equals -3 $\left(-3=\frac{-0.03}{0.01}\right)$, on average. This elasticity exceeds that observed for the effects caused by reductions in AI_i. and AS_i, on the link between scarcity disclosure and daily sales – as estimated based on the γ_I and γ_s coefficients for ln(AI) • SM and ln(AS) • SM in Panel C in Table 6 (γ_I = -0.119 and γ_s = -0.106). For an SKU with an average AI_i and an average AS_i, ($e^{1.55} = 4.71$ days and $e^{0.99} = 2.69$ units, respectively in Table 5), a unit decrease in AI_i and AS_i corresponds to a decrease in AI_i and AS_i of 21.23% and 37.17%, respectively. In turn, according to the values estimated for γ_I and γ_s, these reductions will ameliorate the adverse impact by scarcity disclosure on daily sales by 5.40% $\left(e^{(\gamma_I * \ln(4.71) - \gamma_I * \ln(3.71))}\right)$ and 4.80% $\left(e^{(\gamma_S * \ln(2.69) - \gamma_S * \ln(1.69))}\right)$, respectively. When we compare these effects against the percentage decreases in AI_i and AS_i responsible for them, we see that they only amount to a fraction $\left(\frac{5.40}{-21.23} = -0.25 \text{ and } \frac{4.80}{-37.17} = -0.13\right)$ of the decreases in AI_i and AS_i. Although these ratios will rise for SKUs with AI_i and AS_i values increasingly above their corresponding sample averages, they will only match the ratio estimated for price elasticity in daily sales (-3) at relatively high levels of AI_i (55.55) and AS_i (62.50). Therefore, based on the estimated price elasticity for daily sales, price discounts are relatively more effective at offsetting the negative effect on daily sales induced by scarcity messages' disclosure than reductions in AI_i and AS_i across a wide range of SKUs are.

7. Conclusions

In this paper, we have examined the impact that posting scarcity messages online has on inter-purchase time and daily sales. To that end, we focused on an online retailer selling durable goods to consumers over multiple inventory replenishment cycles, without restrictions as to the amount of time these products are available for sale and the number of units per product consumers can buy in the same order. By focusing on this particular setting, we were able to obtain insights that are generalizable to markets in which retailers sell consumer goods for which purchase quantities will vary depending on consumers' needs.

Our results showed that the disclosure of inventory upper bound information via these scarcity messages can increase a product's frequency of purchase. Furthermore, this increase appears to take effect upon the disclosure of these messages to consumers and remains consistent during the time the messages are available. Limitations in inventory availability do not seem to censor significantly this effect. These findings follow from expectations that information signaling low inventory availability can create perceptions of scarcity among consumers that will induce them to buy. On average, the disclosure of these messages increases the frequency of purchase for SKUs by an average of 14.80%, after controlling for SKU fixed effects.

Nevertheless, when we partialed out moderation effects by SKUs' average purchase frequencies and average daily sales quantities, we found that the magnitude of the scarcity disclosure effect on purchase frequencies depends on how slowly items move in relation to other products. Only items at the bottom 51 percentile of the purchasing frequency distribution in our sample exhibit this effect. Reductions in SKU prices will expand this percentile to include faster moving items. However, these discounts will erode firm profitability. The fact that the disclosure of scarcity messages will have a positive effect on purchase frequencies among SKUs that exhibit a relatively low incidence of purchase and are priced aggressively relative to other SKUs in the assortment may explain why scarcity disclosure strategies are often used in flash sales settings in which retailers frequently market loss-leader SKUs to consumers.

We also found that the disclosure of scarcity messages decreases SKUs' daily sales quantities. On average, the disclosure of scarcity messages decreases these amounts by an average of 17.60%, after controlling for SKU fixed effects. However, when we partialed out moderation effects by SKUs' average purchase frequencies and average daily sales quantities, we found that this effect is less pronounced for items that are sold in small quantities. Furthermore, our analysis revealed that, price discounts are particularly effective in offsetting the negative effect on daily sales induced by scarcity messages' disclosure among SKUs sold in larger amounts.

Together, these findings provide boundary conditions to the effects on sales caused by the disclosure of inventory information as well as price discounts to consumers when selling durable goods online. It is evident from these conditions that sales reactions to stimuli conveyed by the disclosure of scarcity messages are nontrivial and that these reactions are contingent on SKUs' frequencies of purchase, daily sale amounts, and prices. An indiscriminate implementation of scarcity disclosure strategies across products will lead to suboptimal results. To be effective in increasing daily sales, these strategies must focus on SKUs that are typically purchased by consumers in relatively small quantities as well as marketed by retailers at competitive prices. These findings offer clear practical implications for retailers when considering how to stimulate sales through a combination of SKU scarcity signals and prices.

Our results also provide several implications for researchers who are interested in expanding on our study. Additional research may focus on product categories different from those considered in our analysis. Studies involving home improvement products such as those sold by retailers like Lowe's or Home Depot may offer additional insights into the role of scarcity messages in shaping demand for SKUs typically purchased by consumers in larger sets, compared to those in our study. It is possible that the adverse impact by scarcity messages on daily sales we observed will be more prominent in these settings. Another opportunity for future research is the evaluation of alternative inventory thresholds for the disclosure of scarcity messages. This would provide retailers with an understanding of the optimal threshold policy they should use for the disclosure of scarcity messages. Thresholds may vary as a function of SKUs' average inter-purchase times, daily sales, and prices. A third avenue for additional research may involve an evaluation of the impact of price competition among retailers on the effectiveness of scarcity disclosure in influencing demand across SKUs. This is a particularly relevant issue for retailers operating online under slim price margins. It is possible that demand for SKUs under these conditions may not be as sensitive to the disclosure of scarcity messages. Finally, future work may consider the availability of SKUs in online and offline channels operated by the same retailer as part of the evaluation of scarcity disclosure strategies online. Our research focused on a sample of SKUs offered only online. However, it is possible that expanding the sample to include SKUs offered online as well as at brick and mortar stores will show a reduction in the effect of scarcity messages on demand.

References

Angrist, J.D.; Pischke, J.S., 2008. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press, Princeton, NJ.

Anderson, M., Dobkin, C., Gross, T., 2012. The effect of health insurance coverage on the use of medical services. American Economic Journal: Economic Policy. 4 (1), 1–27.

Aviv, Y., Tang, C.S., and Yin, R., 2009. Mitigating the adverse impact of strategic waiting in dynamic pricing settings: a study of two sales mechanisms. In Netessine, S., Tang, C.S. (Eds.) Consumer-Driven Demand and Operations Management Models (353-370). Springer, New York, NY.

Bakos, J. Y. 1997. Reducing buyer search costs: Implications for electronic marketplaces. Management Science. 43 (12), 1676-1692.

Balakrishnan, A., Pangburn, M.S., Stavrulaki, E. 2004. 'Stack them high and let them fly': lot-sizing policies when inventories stimulate demand. Management Science. 50 (5), 630–644.

Balakrishnan, A., Pangburn, M.S., Stavrulaki, E. 2008. Integrating the promotional and service roles of retail inventories. Manufacturing and Service Operations Management. 10 (2), 218-235.

Boada-Collado, P., Martinez-de-Albeniz, V. 2017. Estimating and optimizing the impact of inventory on consumer choices in a fashion retail setting. Working Paper. IESE Business School, University of Navarra (https://pdfs.semanticscholar.org/2254/fbb8c5b1255168e4843c2413fb4f9c6573a0.pdf).

Boyer, K.K., Hallowell, R., Roth, A.V., 2002. E-services: operating strategy — a case study and a method for analyzing operational benefits. Journal of Operations Management 20 (2), 175–188.

Brock, T.C. 1968. Implications of commodity theory for value change. In A.G. Greenwald, T.C., Brock, T.M., Ostrom (Eds.), Psychological Foundations of Attitudes (243-275). Academic Press: New York, NY.

Brynjolfsson, E., Smith, M.D. 2000. Frictionless commerce? A comparison of Internet and conventional retailers. Management Science 46 (4), 563-585.

Cachon, G. P., Gallino, S., Olivares, M. 2018. Does adding inventory increase sales? Evidence of a scarcity effect in U.S. automobile dealerships. Management Science (Forthcoming).

Chevalier, J., Goolsbee, A. 2003. Measuring prices and price competition online: Amazon.com and BarnesandNoble.com. Quantitative Marketing and Economics 1 (2), 203-222.

Coviello, D., Guglielmo, A., Spagnolo, G. 2018. The effect of discretion on procurement performance. Management Science 64 (2), 715–738.

Cox, D. R. 1972. Regression models and life tables (with discussion). Journal of the Royal Statistical Society, Ser. B, 34, 187-220.

Cui, R., Zhang, D., Bassamboo, A. (2018). Learning from inventory availability information: evidence from field experiments on Amazon. Management Science (Forthcoming).

Cui, R., Shin, H., 2017. Sharing aggregate inventory information with customers: strategic cross-selling and shortage reduction. Management Science 64 (1), 381-400.

DeGraba, P. 1995. Buying frenzies and seller-induced excess demand. The RAND Journal of Economics 26 (2), 331-342.

Ferreira, K., Lee, B.H., Simchi-Levi, D. 2016. Analytics for an online retailer: demand forecasting and price optimization. Manufacturing & Service Operations Management 18 (1), 69–88.

Fisher, M., Gallino, S., Li, J. 2017. Competition-based dynamic pricing in online retailing: A methodology validated with field experiments. Management Science 64 (6), 2496-2514.

Greene, W. H. (2003). Econometric analysis. Pearson Education, Upper Saddle River, New Jersey.

Ho, T-H; Lim, N., Reza, S, Xia, X. 2017. OM forum: causal inference models in operations management. Manufacturing & Service Operations Management 19 (4), 509-525.

Jerath K, Netessine S, Veeraraghavan, S.K. 2010. Revenue management with strategic customers: last minute selling and opaque selling. Management Science 56 (3), 430–448.

Koschat, M. A. 2008. Store inventory can affect demand: empirical evidence from magazine re-tailing. Journal of Retailing 84 (2), 165-179.

Lynn, M. 1991. Scarcity effects on value: a quantitative review of the commodity theory literature. Psychology & Marketing 8 (1), 43-57.

Netessine, S., Tang, C.S. 2009. Consumer-driven demand and operations management models: a systematic study of information-technology-enabled sales mechanisms. Springer, New York, NY.

Olson, J. R., Belohlav, J.A., Boyer, K. K. 2005. Operational, economic and mission elements in not-for-profit organizations: the case of the Chicago Symphony Orchestra. Journal of Operations Management 23(2), 125-142.

Olson, J. R., Boyer, K. K. 2003. Factors influencing the utilization of Internet purchasing in small organizations. Journal of Operations Management 21(2), 225-245.

Rabinovich, E., Sinha, R., Laseter, T. 2011. Unlimited shelf space in Internet supply chains: treasure trove or wasteland? Journal of Operations Management 29(4), 305-317.

Rao, S.; Griffis, S. E.; Goldsby, T. J. 2011. Failure to deliver? Linking online order fulfillment glitches with future purchase behavior. Journal of Operations Management 29 (7-8), 692-703.

Rao, S., Rabinovich, E., Raju, D. 2014. The role of physical distribution services as determinants of product returns in Internet retailing. Journal of Operations Management 32 (6), 295-312.

Rosenzweig, E. D., Laseter, T. M., Roth, A.V. 2011. Through the service operations strategy looking glass: Influence of industrial sector, ownership, and service offerings on B2B e-marketplace failures. Journal of Operations Management 29 (1-2), 33-48.

Sodero, A., Rabinovich, E. 2017. Demand and revenue management of deteriorating inventory on the Internet: an empirical study of flash sales markets. Journal of Business Logistics 38 (3), 170-183.

Sodero, A., Rabinovich, E., Aydinliyim, T., Pangburn, M.S. 2017. An empirical analysis of how inventory levels and prices affect online retail sales. SSRN Electronic Journal. 10.2139/ssrn.2872938.

Smith, M. D., Brynjolfsson, E. 2001. Customer decision making at an Internet shopbot: brand still matters. Journal of Industrial Economics 49(4), 541-558.

Urban, T. L. 2005. Inventory models with inventory-level-dependent demand: A comprehensive review and unifying theory. European Journal of Operational Research 162(3), 792-804.

Wagner, L., Calvo, E., Cui, R. 2018. The value of disclosing product availability on retail platforms. SSRN Electronic Journal. 10.2139/ssrn.3195047.

Wolfe, H. B. 1968. A model for control of style merchandise. Industrial Management Review 9 (2), 69-82.

Wooldridge, J.M. 2010. Econometric Analysis of Cross Section and Panel Data, Second Edition, The MIT Press, Cambridge, MA.

Zhang, J., Fang, X., Sheng, O. 2006. Online consumer search depth: theories and new findings. Journal of Management Information Systems 23(3), 71-95.

Appendix

A. Data Evaluation

Table A1 presents the distribution of the number of orders and minimum inter-purchase times across order quantities from the data we collected online. To parse through BT's website and collect the data, we used web crawlers operated by Cartbound, a platform offering retail data monitoring services. These web crawlers did not schedule their data collection to run against the retailer's website on a daily basis or any pre-set schedule. Instead, they collected the data as changes in product prices and inventory information occurred. This is reflected in the fact that most SKUs in our sample (174/199 SKUs) have minimum inter-purchase times lower than or equal to 1 day (Table A1). Moreover, for 19 of the 25 SKUs with minimum inter-purchase times exceeding 1 day, the majority of the sales we recorded equaled one unit. It is obviously not feasible to have an aggregation of multiple purchases when sales equal 1 unit. Thus, it is unlikely that our measurements of daily sales will be biased by the aggregation of sales over multiple days such that sales for some days are recorded as zero when in fact they are greater than zero while non-zero sales recorded for other days are higher than the sales amounts that actually took place on those days.

Nevertheless, it is possible that although we recorded changes in inventory as they occurred, some of these changes were the result of multiple purchases that took place on different days but were processed by the retailer on the same day. As a result, our measurements for the dependent variable corresponding to inter-purchase time (in days) may be inflated relative to the actual intervals between orders placed by consumers at the retailer's site. However, this is unlikely for most SKUs in our sample (137/199 SKUs) because most of their purchase quantities (53.13% on average) involved only one unit (Table A1). In addition, based on the 6,794 observations in the panel we used to evaluate inter-purchase time, almost 45% of purchase quantities were only for 1 unit. Moreover, almost 41% of purchase quantities for more than 1 unit had inter-purchase times lower than or equal to 1 day (Figure A1). Therefore, even if these observations included more than one purchase, our unit of measurement in days should provide sufficient granularity to measure inter-purchase times unbiasedly.

Despite this evidence, we tested the Demand Effect by the disclosure of scarcity messages on inter-purchase time with only those observations involving purchase quantities of 1 unit and, therefore, eliminated any potential bias described above inter-purchase time. Furthermore, to control for any censoring biases imposed on inter-purchase time when inventory levels are lower than the amount of units consumers are seeking to purchase, we only considered in this analysis instances when inventory levels were greater than or equal to 2 units. A comparison of the results from this analysis (available upon request) with those reported on the body of the paper showed consistency among the estimated coefficients, including those corresponding to the scarcity-disclosure effects on inter-purchase time.

SKU	Number of Orders for:						Min Inter-Purchase Time for Orders for:					
	1 unit	2 units	3 units	4 units	5 units	6+ units	1 unit	2 units	3 units	4 units	5 units	6+ units
1	27	24	11	7	2	9	1	1	1	1	3	1
2	5	4	0	0	0	0	0	1				
3	16	9	7	3	2	2	3	3	2	3	4	4
4	8	1	1	0	0	0	1	2	1			
5	7	4	2	1	0	2	1	1	1	68		1
6	38	9	4	1	1	0	1	1	1	1	1	
7	29	30	15	7	2	5	0	1	1	1	2	2
8	1	1	0	0	1	4	1	1			1	1
9	1	1	1	0	0	0	214	10	3			
10	9	7	3	0	1	2	1	1	1		2	1
11	2	3	2	1	0	1	1	1	1	1		3
12	10	24	3	6	1	2	1	1	2	1	6	2
13	12	3	6	1	1	1	1	0	0	1	1	1
14	2	3	2	3	3	28	1	1	1	1	1	1
15	23	14	12	6	2	11	1	1	0	1	4	0
16	7	5	4	1	0	1	0	1	3	4		4
17	13	8	2	0	0	1	1	1	1			8
18	5	6	6	3	0	3	2	3	2	4		2
19	5	1	1	0	1	2	1	5	1		5	4
20	8	5	3	1	1	10	1	1	1	1	3	1
21	86	28	10	2	2	0	0	1	0	1	1	
22	15	5	3	0	3	3	0	1	1		1	1
23	10	12	4	1	2	4	2	2	3	11	4	4
24	16	2	0	0	1	0	2	17			12	
25	5	2	3	2	2	4	1	9	3	3	4	4
26	21	4	3	3	0	0	1	1	2	1		
27	14	12	1	4	0	2	1	1	1	1		1
28	0	2	2	0	1	0		1	1		1	
29	0	1	1	0	0	4		3	1			1
30	17	12	5	3	3	4	1	1	3	7	5	3
31	3	4	3	0	0	0	3	1	1			

SKU	Number of Orders for:						Min Inter-Purchase Time for Orders for:					
	1 unit	2 units	3 units	4 units	5 units	6+ units	1 unit	2 units	3 units	4 units	5 units	6+ units
48	5	2	0	0	0	0	3	1				
49	3	5	1	6	7	39	1	1	1	1	1	1
50	12	6	3	2	0	2	1	3	3	3		4
51	9	9	2	2	0	1	1	1	1	1		1
52	18	23	7	7	1	5	1	1	1	1	4	1
53	35	15	3	0	2	1	1	1	8		5	1
54	11	5	2	2	1	1	2	2	1	4	8	3
55	40	10	9	5	2	9	0	1	2	1	1	1
56	12	5	3	2	2	1	1	1	1	3	2	51
57	0	0	0	0	0	6						1
58	14	16	8	1	2	6	0	2	2	5	4	3
59	4	1	1	0	0	0	1	1	2			
60	1	2	0	0	0	3	9	4				1
61	0	6	2	1	0	0		1	1	3		
62	9	5	9	5	5	20	1	1	1	1	1	1
63	2	6	1	1	0	0	1	0	0	0		
64	17	15	7	1	2	1	1	1	1	8	1	4
65	10	9	3	5	4	17	1	0	1	1	1	1
66	7	1	0	0	1	0	1	17			39	
67	4	3	5	0	1	7	1	0	1		1	1
68	11	0	0	1	0	0	1			22		

Table A1 – Number of Orders and Minimum Inter-Purchase Times across Order Quantities

SKU	Number of Orders for:						Min Inter-Purchase Time for Orders for:					
	1 unit	2 units	3 units	4 units	5 units	6+ units	1 unit	2 units	3 units	4 units	5 units	6+ units
95	0	0	2	0	0	2			2			0
96	2	4	0	0	0	0	1	1				
97	7	6	1	0	0	1	2	1	27			22
98	8	8	4	0	0	0	1	2	1			
99	5	6	1	1	1	2	1	2	1	1	1	1
100	26	11	12	7	2	5	1	1	1	1	2	1
101	2	0	0	0	0	1	5					2
102	60	26	9	3	2	0	1	1	1	1	1	
103	8	4	1	1	1	5	1	1	3	3	1	1
104	2	1	0	2	1	0	1	3		1	1	
105	19	18	3	1	0	4	1	2	1	1		2
106	72	45	40	9	7	4	1	1	0	1	1	1
107	3	5	9	3	9	47	1	1	2	2	1	1
108	19	1	0	0	0	0	1	5				
109	2	2	2	0	0	0	5	10	3			
110	10	1	1	0	0	0	3	17	4			
111	11	12	4	4	3	2	1	1	1	1	1	1
112	10	20	3	3	1	3	1	1	4	2	8	1
113	54	27	7	3	2	7	1	1	1	1	4	2
114	6	0	2	0	0	0	1		2			
115	9	0	0	0	0	0	0					
116	39	22	7	5	3	3	0	1	1	1	1	1
117	26	14	9	4	9	22	1	1	1	1	0	1
118	1	0	0	0	0	2	1					3
119	6	1	6	3	6	9	0	1	1	1	1	1
120	2	2	0	0	0	0	1	1				
121	25	6	3	1	0	1	0	3	3	4		3
122	9	9	4	0	2	5	1	0	1		2	1
123	0	4	0	0	0	3		2				0
124	11	6	1	1	0	4	1	0	2	2		1
125	6	11	7	5	3	5	1	1	1	1	0	1
126	17	10	4	3	1	1	0	1	1	1	0	1
127	7	3	0	0	1	0	1	2			11	
128	6	20	9	1	3	11	1	1	1	4	1	1
129	30	15	9	2	2	1	1	1	1	2	1	9
130	11	7	2	0	0	0	1	2	2			
131	11	3	1	1	0	2	1	1	5	9		1
132	13	5	8	3	0	4	2	2	2	3		4
133	7	5	2	1	2	2	1	0	1	1	1	1
134	16	1	3	0	0	0	0	19	7			
135	11	4	2	2	0	4	1	1	1	1		1
136	6	1	1	0	0	1	1	3	6			1
137	9	5	0	0	0	0	2	1				
138	8	3	0	2	1	0	1	1		1	1	
139	16	4	4	1	0	3	2	3	4	16		3
140	28	10	1	1	0	2	1	2	3	9		2
141	0	1	1	1	0	3		3	7	3		4
142	17	1	0	0	0	0	0	7				
143	9	7	3	1	8	3	3	3	3	4	3	3
144	4	2	0	1	1	0	1	1		1	1	
145	8	2	1	0	1	1	1	2	1		1	7
146	18	4	3	1	0	1	1	1	1	3		8
147	2	4	1	3	0	12	2	1	1	1		1
148	9	0	1	1	0	1	1		8	46		3
149	3	0	1	1	1	4	4		4	15	7	0
150	8	7	0	5	2	5	1	1		1	1	1
151	3	3	0	0	0	12	1	1				1
152	6	5	2	0	0	1	1	1	1			6
153	0	1	0	0	0	0		1				
154	4	2	5	2	4	16	1	1	1	2	1	1
155	8	8	2	0	3	0	3	3	3		3	
156	5	8	4	2	0	0	4	2	3	3		
157	10	4	3	2	5	10	1	1	1	1	1	0
158	29	8	2	0	0	0	1	1	5			
159	11	6	3	1	1	1	1	3	5	10	14	4
160	30	18	13	3	2	1	0	1	2	2	2	2
161	13	5	3	2	0	1	0	1	1	1		8
162	7	1	1	1	0	2	0	14	4	1		1
163	58	15	3	0	0	0	1	1	1			
164	9	3	4	2	2	1	0	1	1	1	1	4
165	4	3	0	0	2	12	1	1			2	1
166	6	4	6	6	10	23	1	1	1	1	2	1
167	10	2	7	5	1	10	1	1	1	1	2	1
168	14	12	7	9	8	17	1	1	1	1	1	1
169	7	6	0	2	0	0	1	1		3		
170	1	2	0	1	1	3	28	7		7	4	1
171	24	10	5	2	2	1	1	1	2	2	3	7
172	34	16	10	4	0	1	0	1	1	1		1
173	10	7	5	8	1	4	1	1	1	0	3	1
174	10	5	3	1	3	3	1	1	1	5	1	1
175	15	6	5	3	1	1	1	1	1	1	3	1
176	0	0	1	1	0	5			3	1		1
177	19	17	5	4	2	6	1	1	1	4	3	1
178	6	2	0	0	0	3	1	3				1
179	9	4	3	1	1	2	3	3	2	3	11	0
180	6	2	0	0	0	0	2	6				
181	6	20	20	15	11	21	1	1	1	1	0	2
182	2	2	3	1	0	6	2	1	1	1		1
183	4	3	4	3	1	1	2	4	3	3	3	3
184	7	4	0	0	0	0	2	1				
185	31	7	1	0	0	0	2	2	7			
186	5	4	4	2	1	6	2	3	2	5	14	5
187	6	3	6	2	0	20	1	1	1	1		0
188	11	6	6	3	3	16	0	1	0	0	1	0
189	5	0	0	0	1	2	3				12	1
190	2	5	2	6	7	38	1	1	1	1	2	1
191	8	3	0	0	0	0	3	1				
192	44	24	12	9	9	9	1	1	1	1	1	1
193	26	23	15	6	2	9	0	1	1	1	1	1
194	9	2	1	0	3	1	1	3	1		1	1
195	1	0	0	0	0	2	3					1
196	26	17	10	1	3	8	0	0	1	1	2	1
197	4	14	4	6	2	0	1	1	1	1	1	
198	6	4	5	3	0	0	1	1	1	2		
199	14	8	2	6	1	4	1	1	1	1	1	1

Table A1 – Number of Orders and Minimum Inter-Purchase Times across Order Quantities

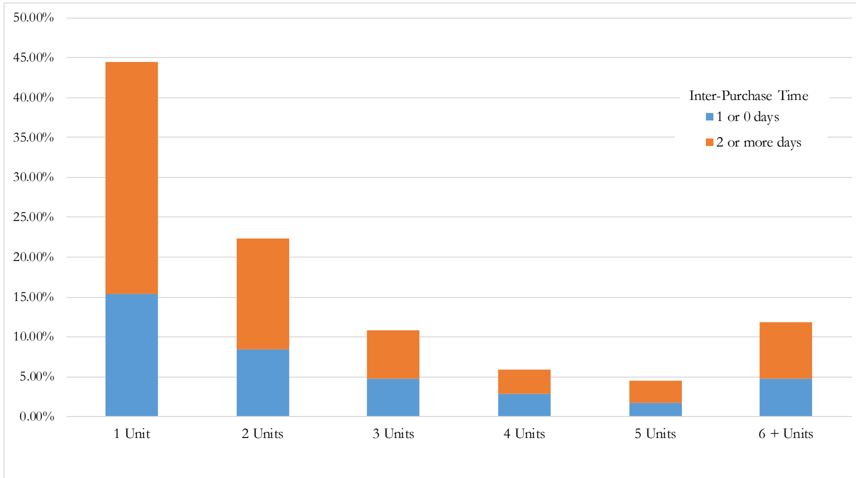

Figure A1—Histogram of Purchase Quantities Conditional on Inter-Purchase Times

B. Results from Alternative Modeling Specifications

We first evaluate the robustness of the results in Section 5 by estimating the same models in Equations (1) and (2) using different specifications for the dependent variables, inter-purchase time and daily sales, instead of using log transformations. As the estimation results reported in Table B1 show, we find consistent results regarding the price and the scarcity message effects, adding validity to our findings.

Fixed Effect Dummy Least Square						
Parameter	*Dependent Var.: IPT*			*Dependent Var.: Sales*		
	Estimate	*SE*	*t-val.*	*Estimate*	*SE*	*t-val.*
***Relative Price** for IPT* (δ)	0.016***	0.003	4.898			
***Price** for Sales* (δ)				-0.245**	0.120	-2.034
Scarcity Message (γ)	-0.889**	0.380	-2.338	-0.531***	0.078	-6.836
SKU Fixed Effect (α_i)		Yes			Yes	
Month Fixed Effect (β_m)		Yes			Yes	
F statistic		4.939***			8.04***	
R-squared		0.14			0.06	
Adj. R-squared		0.11			0.05	
Number of Obs.		6,794			27,044	

Clustered standard errors are used. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Table B1 – Robustness Check Using Alternative Model Specification of Equations (1) and (2)

In addition, we interpreted inter-purchase time as the "survival time" of "no purchases" in the context of survival analysis and used the ***Cox Proportional Hazard Model*** (Cox, 1972) to estimate the hazard rate of inter-purchase time z (i.e., no purchases over z days) according to Equation (B1):

$$h(IPT_{it} = z \mid X_{it}) = h_0(z) \cdot \exp(\alpha_i + \sum_m \beta_m \cdot I(t \in m) + \gamma \cdot SM_{it} + \delta \cdot RP_{it}), \qquad \text{(B1)}$$

where, $h(\cdot \mid X_{it})$ is the hazard rate associated with different covariates $\boldsymbol{X}_{it}$ (e.g., SM_{it}, RP_{it}) and $h_0(z)$ denotes the "baseline hazard." Also, we can interpret the estimated value exp(γ) as the "hazard ratio" that specifies the impact of scarcity messages on the inter-purchase time z: the scarcity message increases hazard if exp(γ) > 1 and reduces the hazard if exp(γ) < 1. Similarly, the term exp (δ) represents the hazard ratio associated with the impact of relative price.

We report maximum-likelihood estimation results for Equation (B1) in Table B2. First, we observe that exp(δ) = exp(-0.172) < 1 and exp(γ) = exp(0.081) > 1 so that the hazard rate decreases with relative price and increases with the disclosure of scarcity messages. Specifically, with the scarcity message, the hazard rate increases from 1 (baseline) to 1.084 (hazard rate= exp(0.081)= 1.084, p-val.= 0.055), which implies that the inter-purchase time duration decreases by 8.4%. Moreover, a unit increase in relative price decreases the hazard rate from 1 (baseline) to 0.841 (hazard rate= exp(-0.171) = 0.843, p-val. = 0.01). Consequently, the inter-purchase time duration increases by 15.7%.

	Cox Hazard Model		
Parameter	***Dependent Var.: IPT***		
	Estimate	***SE***	***t-val.***
Relative Price *for IPT* (δ)	-0.172***	0.046	-3.723
Scarcity Message (γ)	0.081*	0.044	1.830
SKU Fixed Effect (α_i)	Yes		
Month Fixed Effect (β_m)	Yes		
Log-likelihood	-54,125		
AIC	108,288		
BIC	108,418		
Number of Obs.	6,794		

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Table B2 – Robustness Check Using Cox Proportional Hazard Model

Furthermore, we modeled daily sales as a count variable using (i) a ***Poisson***, (ii) a ***Negative Binomial***, and (iii) a ***Zero-Inflated Negative Binomial*** regression model. A Poisson model is a generalized linear model of regression analysis (Greene 2003) – as shown in Equation (B2):

$$Pr(Sales_{id}=s|X_{id}) = Poisson(a+\sum_m \beta_m \cdot I(d \in m) + \gamma \cdot SM_{id} + \delta \cdot ln(P_{id})) \quad \text{(B2)}$$

where s denotes the number of units sold for SKU i on day d (count). Equation (B2) assumes that daily sales are based on a Poisson random variable with a rate associated with different covariates in X_{id} (e.g., SM_{id}, P_{id}). Thus, Equation (B2) states that the probability of observing s follows the Poisson probability density function associated with those covariates in X_{id} (e.g., SM_{id}, P_{id}). Here, the estimated values exp(γ) and exp(δ) represent the impact of scarcity messages and price on expected daily sales, respectively.

The Poisson regression model has been criticized for its restrictive property that the conditional variance equals the conditional mean (i.e. over-dispersion problem). The Negative Binomial model tackles this problem by introducing an unobserved heterogeneity term which follows a gamma distribution. We estimate the following negative binomial regression model:

$$Pr(Sales_{id}=s|X_{id},\varkappa_{id}) = \varkappa_{id} \cdot Poisson(a+\sum_m \beta_m \cdot I(d \in m) + \gamma \cdot SM_{id} + \delta \cdot ln(P_{id})) \quad \text{(B3)}$$

where $\varkappa_{id} \sim gamma(\frac{1}{\eta}, \frac{1}{\eta})$ distribution with E($\varkappa_{id}$)=1 and V($\varkappa_{id}$)=η. Note $\varkappa_{id}$ captures both cross-sectional and serial unobserved heterogeneity added to the Poisson regression part, adding flexibility to the model.

In addition to over-dispersion and unobserved heterogeneity, count data are often characterized by excess zeros. To additionally account for this, we consider the following Zero-Inflated Negative Binomial regression model:

$$Sales_{id} \sim \begin{cases} 0 & \text{with probability} \quad \Phi(Z_{id} \cdot \vartheta) \\ Negative\ Binomial\ (Sales_{id}=s|X_{id}) & \text{with probability} \quad 1\text{-}\Phi(Z_{id} \cdot \vartheta)' \end{cases} \quad \text{(B4)}$$

where *Negative Binomial*($Sales_{id}=s/X_{id}$) represent the negative binomial regression model specified in Equation (B3) and $\Phi(Z_{id} \cdot \vartheta)$ is the zero inflation model which captures the excessive zero observations. The Zero Inflation model is specified as a function of observed covariates Z_{id} and ϑ is a vector of parameters. Since $\Phi(Z_{id} \cdot \vartheta)$ should be a valid probability bounded between zero and one, we specify a standard normal distribution function for $\Phi(\cdot)$ and use the same covariates as X_{id} for Z_{id}.

We report maximum-likelihood estimation results for the three count data models specified in Equations (B2)-(B4) in Table B3. From the Poisson regression results, we find that both the effect of price and the effect of scarcity message disclosure on daily sales are negative and statistically significant. This suggests that, relative to baseline conditions with no scarcity messages (i.e. exp ($\gamma \cdot SM_{id}$) = exp (0) = 1), the disclosure of these messages can reduce expected daily sales shrink by 68% (exp ($\gamma \cdot SM_{id}$) = exp (-1.151) = 0.32). Similarly, when log-price ($\ln(P_{id})$) increases by a unit, daily sales decrease by 16% (exp (δ) = exp (-0.281) = 0.84).

	Poisson Regression			*Negative Binomial Regression*			*Zero-Inflated Negative Binomial Regression*		
Parameter	*Dependent Var.: Sales*			*Dependent Var.: Sales*			*Dependent Var.: Sales*		
	Est.	***SE***	***t-val.***	***Est.***	***SE***	***t-val.***	***Est.***	***SE***	***t-val.***
Price ($\boldsymbol{\delta}$)	-0.175***	0.010	-18.30	-0.112***	0.028	-3.90	-0.103***	0.030	-3.50
Scarcity Message ($\boldsymbol{\gamma}$)	-1.151***	0.022	-52.30	-1.173***	0.046	-25.50	-0.324***	0.074	-4.40
Gamma dist. Parameter (η)				8.541***	0.159	53.70	7.478***	0.148	50.60
Zero-inflation model - Constant (ϑ_0)							-6.955***	0.142	-49.10
Zero-inflation model - Price (ϑ_1)							0.048	0.050	1.00
Zero-inflation model - Scarcity Message (ϑ_2)							6.853***	0.142	48.40
Month Fixed Effect	Yes			Yes			Yes		
Log-likelihood	-54,959			-24,533			-24,378		
AIC	109,956			49,105			48,801		
BIC	110,112			49,269			48,990		
Number of Obs.	27,044			27,044			27,044		

** and *** denote statistical significance at 5% and 1% levels respectively.

Table B3 – Robustness check using Count Data Models

From the Negative Binomial regression results, we find that both the effect of price and the effect of scarcity message disclosure on daily sales are negative and statistically significant. This suggests that, relative to baseline conditions with no scarcity messages, the disclosure of these messages can reduce expected daily sales by 69% (exp ($\gamma \cdot SM_{id}$) = exp (-1.173) = 0.31). Similarly, when log-price ($\ln(P_{id})$) increases by a unit, daily sales decrease by 11% (exp (δ) = exp (-0.112) = 0.89). The gamma distribution parameter η is highly significant and positive (8.541, p-val.<0.001). Note that when η converges to zero, the Negative Binomial regression model becomes a Poisson regression model. We also observe that, according to all model fit measures (log-likelihood, AIC, and BIC), the Negative Binomial model is preferable to the Poisson model. We can conclude that our daily sales data has substantial unobserved heterogeneity and over-dispersion and thus can be better represented by a Negative Binomial model.

Next, from the Zero-Inflated Negative Binomial regression results, we find that both the effect of price and the effect of scarcity message disclosure on daily sales are negative and statistically significant. When log-price ($\ln(P_{id})$) increases by a unit, daily sales decrease by 10% ($\exp(\delta) = \exp(-0.103) = 0.90$). Relative to baseline conditions with no scarcity messages, the disclosure of these messages can reduce expected daily sales by 28% ($\exp(\gamma \cdot SM_{id}) = \exp(-0.324) = 0.72$). Compared to the two previous model results, this value looks rather small. This is because the scarcity message can influence daily sales through another route – the Zero-Inflation process. The coefficient of scarcity message in the Zero-Inflation model (ϑ_2) is highly significant and positive, indicating that the probability of observing zero versus the Negative Binomial process (which has a mean greater than zero) significantly increases with scarcity messages. More specifically, at the average log price (=5.68), the estimated value of the zero inflation model is 0.56 $(= \Phi(Z_{id} \cdot \vartheta) = \Phi(-6.955 + 0.047*5.68 + 6.853))$ when the scarcity message is on, while this number shrinks to 0 when the message is off $(0 = \Phi(Z_{id} \cdot \vartheta) = \Phi(-6.955 + 0.047*5.68))$. Again, our estimation result confirms that the scarcity message has a negative impact on daily sales through both a Negative Binomial process and a Zero Inflation process. The gamma distribution parameter η is highly significant and positive (7.478, p-val. < 0.001). We also observe that the Zero-Inflated Negative Binomial model is the most preferred among three models in terms of three fit measures (log-likelihood, AIC, and BIC).

In summary, using a Cox Proportional Hazard model and three count data models, we re-examine the effects of scarcity messages on demand and reach the same conclusions as in Section 5. First, we observe that the disclosure of these messages reduces the inter-purchase time for the SKUs. In addition, we find that the disclosure of these messages decreases daily sales.

C. Results Excluding SKUs with Extended Stockout Observations

As we explained before, 1,634 SKU-day observations involved the occurrence of stockouts with an available inventory of zero units. Because consumers cannot purchase products during these periods, we removed these observations from consideration in our analyses. Furthermore, we observed that most of these stockouts involved only 20 SKUs for which the total days of stockouts was above 10% of their observation periods. It is possible that the reason most stockouts involved these SKUs is that they were subject *a priori* to lower fill rate targets relative to those for the rest of the SKUs in the sample. Consequently, because demand measures may be "biased" by the inclusion of these SKUs, we constructed a new dataset in which we excluded them from consideration and then used this dataset to re-estimate the RDD model in Equations (3) and (4). As we show in Table C1, the results we obtained from this revised dataset are consistent with those in Table 4. Thus, our results are robust to noises or random shocks in demand due to potential differentials in fill rate policies across the SKUs in the sample.

	Dependent Var.: ln(IPT+1)			*Dependent Var.: ln(Sales+1)*		
Parameter	***Estimate***	***SE***	***t-val.***	***Estimate***	***SE***	***t-val.***
Relative Price *for IPT*	0.129***	0.035	3.683			
Price *for Sales*				-0.067***	0.015	-4.469
Scarcity Message	-0.160**	0.067	-2.395	-0.155***	0.017	-9.092
θ	0.0005***	0.0002	3.038	0.000	0.000	-0.911
ρ	-0.040**	0.020	-2.038	0.009	0.006	1.623
SKU Fixed Effect	Yes			Yes		
Month Fixed Effect	Yes			Yes		
F statistic	13.987***			22.983***		
R-square	0.327			0.154		
Adj. R-square	0.304			0.147		
Number of Obs.	6,095			23,439		

Clustered std. errors are used. ** and *** denote statistical significance at the 5% and 1% levels, respectively

Table C1 – Estimation results using RDD

D. Results from Alternative RDD Specifications for Heterogeneity Effects

We use *HighAS* as an indicator variable that takes a value of 1 if the average daily sales of an SKU *i* is greater than the median of average daily sales of all sample products, or zero otherwise. Similarly, *HighAI* is an indicator variable that takes a value of 1 if the average inter-purchase time of a SKU *i* is greater than the median of the average inter-purchase times of all sample products, or zero otherwise. Table D1 presents the results. These results are consistent to those in Table 6 (in Section 5).

Panel A	Dependent Var.: ln(IPT+1)			Dependent Var.: ln(Sales+1)		
Parameters	*Estimate*	*SE*	*t-val.*	*Estimate*	*SE*	*t-val.*
Relative Price *for IPT* (δ)	0.148***	0.032	4.598			
Price *for Sales* (δ)				-0.028**	0.014	-2.045
Scarcity Message (γ_0)	-0.148**	0.065	-2.260	-0.109***	0.017	-6.404
HighAS• SM (γ_S)	-0.001	0.056	-0.013	-0.189***	0.018	-10.278
θ	0.001***	0.000	3.548	-0.0003**	0.0001	-3.124
ρ	-0.027	0.019	-1.467	-0.010**	0.005	-2.004
SKU Fixed Effect (α_i)		Yes			Yes	
Month Fixed Effect (β_m)		Yes			Yes	
F statistic		13.26***			23.49***	
R-square		0.309			0.152	
Adj. R-square		0.286			0.146	
Number of Obs.		6,794			27,044	
Panel B	**Dependent Var.: ln(IPT+1)**			**Dependent Var.: ln(Sales+1)**		
Parameters	*Estimate*	*SE*	*t-val.*	*Estimate*	*SE*	*t-val.*
Relative Price *for IPT* (δ)	0.146***	0.032	4.545			
Price *for Sales* (δ)				-0.032***	0.014	-2.346
Scarcity Message (γ_0)	-0.054	0.071	-0.759	0.072***	0.026	2.741
HighAI • SM(γ_I)	-0.165***	0.056	-2.965	-0.299***	0.025	-11.818
θ	0.001***	0.000	3.784	0.000	0.000	-1.270
ρ	-0.028	0.018	-1.508	-0.009*	0.005	-1.672
SKU Fixed Effect (α_i)		Yes			Yes	
Month Fixed Effect (β_m)		Yes			Yes	
F statistic		13.32***			23.68***	
R-square		0.310			0.153	
Adj. R-square		0.287			0.147	
Number of Obs.		6,794			27,044	
Panel C	**Dependent Var.: ln(IPT+1)**			**Dependent Var.: ln(Sales+1)**		
Parameters	*Estimate*	*SE*	*t-val.*	*Estimate*	*SE*	*t-val.*
Relative Price *for IPT* (δ)	0.146***	0.032	4.541			
Price *for Sales* (δ)				-0.029**	0.014	-2.112
Scarcity Message (γ_0)	-0.037	0.075	-0.497	0.131***	0.027	4.896
HighAS• SM (γ_S)	-0.042	0.058	-0.729	-0.183***	0.018	-9.982
HighAI • SM (γ_I)	-0.174***	0.057	-3.053	-0.292***	0.025	-11.562
θ	0.001***	0.000	3.710	-0.0003***	0.0001	-2.882
ρ	-0.030	0.019	-1.599	-0.013***	0.005	-2.576
SKU Fixed Effect (α_i)		Yes			Yes	
Month Fixed Effect (β_m)		Yes			Yes	
F statistic		13.26***			24.14***	
R-square		0.310			0.156	
Adj. R-square		0.287			0.150	
Number of Obs.		6,794			27,044	

Clustered standard errors are used. ** and *** denote statistical significance at the 5% and 1% level, respectively.

Table D1 - Estimation Results using RDD Interaction Models