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**On-Shelf Customer Availability Research: The Effects of the Day-of-the-Week, Product,
and Category Characteristics on Stockouts**

by

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**An Honors Thesis in partial fulfillment of the requirements for the degree Bachelor of
Science in Business Administration in Transportation/Logistics.**

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Abstract

This paper seeks to examine the causes of stockouts and on-shelf customer availability by examining various product and category characteristics, as well as the day-of-the-week to study their effects on stockouts. Over 8 weeks, data was collected by taking tri-weekly photographs of three product categories at a retail store, and then the data was extracted to a spreadsheet before empirical analysis was done. The results of the study indicated that the probability of a stockout increased when planned facings decreased, the unit price increased, proper on-shelf placement decreased, and when other SKU's of the same category also stocked out.

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Introduction

As a consumer, there are few scenarios that can ruin a shopping experience more than when a product is not on the shelf. After spending precious time to travel out to a retail store with purchasing a very specific item in mind, to finally arrive at the shelf and to have the product absent from the shelf can be frustrating, to say the least. Additionally, firms also have a large incentive to improve on-shelf availability. There can be many reasons for this, but one reason is because research has shown that shopper loyalty erodes over time when stockouts continually occur (ECR UK 2007; Anderson Consulting 1996). Furthermore, one study reported that 31% of consumers will buy the item at another store if presented with a stockout (Corsten et al. 2003). Another reason why firms have an incentive to improve OSA is simply the risk of potential lost sales (Gruen et al. 2002). The issue of on-shelf customer availability is most certainly a concern for executives, as the same study summarizes the situation by stating “availability of products to the customer is the new battleground in the fast- moving consumer goods industry (Corsten et al. 2003).” In light of this, OSA is definitely an important measurement for retailers (Trautrimis et al. 2009).

One might consider the idea of a SKU being “in-stock” simply meant that the firm’s internal electronic system displayed that the particular store in question had enough inventory on hand to meet its daily demand. However, suppose none of that store’s inventory was actually on the shelf. One could easily argue that on those terms, the product is actually not in-stock, since no actual inventory is placed on the shelf and ready to be purchased. In other words, a product could be “in-stock” without truly being available for purchase by the consumer. With this in mind, the term “on-shelf availability” is derived. In addition, the majority of this research is more concerned with on-shelf availability, as opposed to a product’s “in-stock” metric.

Even though the question of improving on-shelf availability may be enormous, there are still contributions that can be made. In a broad sense, my objective for the study will simply be to gain a greater understanding of the causes of stockouts at the shelf. More specifically, this will be done by gathering empirical data from the retail shelf to perform regression analyses on it to find causal relationships between several variables and the occurrences of stockouts.

Literature Review

Despite the substantial amount of research and effort that has gone into the problem of on-shelf availability over the last few decades, stockout rates have not decreased (Gruen et al. 2002). There also seems to be general consensus on where the issues of stockouts originate. Many sources cite store execution specifically as the main cause (Raman et al. 2001; Gruen et al. 2002; Corsten et al. 2003; Anderson Consulting 1996), casting blame to the retailer to include a variety of duties such as shelf capacity, ordering systems, and store forecasting. These researchers have also devoted attention to the lost sales that occur as a result of stockouts.

The effects of out-of-stocks on sales

To begin with, depending on which study is referenced, the average out-of-stock rate (or stockout rate) seems to hover around 5% -10%, making the most commonly reported average out-of-stock rate to be about 8%-8.5% (Corsten et al. 2003). One study showed that the estimated sales loss in their study to be 3.9% (Corsten et al. 2003). This is not only significant because of the lost sales/profits that firms are experiencing, but also because the issue of on-shelf availability has been a problem for a long time. Despite the large amount of studies that have

been done on the topic, there have virtually been no improvements of on-shelf availability levels for many years.

There are also several potential responses or alternatives to an out-of-stock. A consumer can choose to purchase another item of the same brand, purchase another item of a different brand, delay the purchase, buy the same item at a different store, or simply not purchase the item. A study from ECR (Efficient Consumer Response) done across 8 different categories in 2002 found that 31% of consumers will choose to purchase the same product at another store. From the same study, a reported 26% will choose to buy a competitor's brand as a substitute (Gruen et al. 2002). Of course, this is further evidence to suggest why both retailers and suppliers should (and do) have such a large interest in finding a remedies.

Causes and solutions for out-of-stocks

Many researchers seem to cite retail execution as the main driver of out-of-stocks. As the problem that has also been termed "the last 50 yards" problem, store execution can include store ordering and forecasting or poor shelf re-stocking practices (Gruen et al. 2002). Others have included inaccurate inventory records and misplaced SKUs (stock-keeping units) as significant causes for out-of-stocks (Raman et al. 2001). With regard to inaccurate inventory levels, one study reported that one leading retailer discovered that more than 65% of the inventory records were inaccurate at the store-SKU level. In other words, its physical inventory levels did not reflect what the inventory levels that its computer inventory systems displayed.

Within a study solely focused on retail execution, the 3 categories of drivers that the authors identified of out-of-stocks were replenishment and sales processes at stores and DC's (distribution centers), merchandising and inventory management, and employee turnover (Raman et al. 2001). When a checkout employee scans plain yogurt twice even though your purchase is actually for one item of plain yogurt and one item of lemon yogurt (assuming both products are identically priced), this is an example of a flawed replenishment/sales process because this leads to the items' physical and "system" inventory levels to have a disparity. In the case of merchandising and inventory management, one implication of a store carrying more variety is that there is a much higher risk of execution problems (misplaced SKU's, for example). Holding large amounts of inventory will make keeping an accurate count of inventory a difficult task. Lastly, employee turnover of a store can have a very significant impact on out-of-stocks because newer employees will be less familiar with the replenishment processes and are more prone to making errors while transferring the inventory from the storage areas to the shelves. The remedies discussed in the study were to create awareness of the problem, count and inspect inventory levels, and to set benchmarks within each store to identify how merchandising and inventory management affect store execution.

Others have focused on the retailer's ordering, replenishment, and merchandising practices as the chief causes for out-of-stocks (Anderson Consulting 1996). For warehouse-supplied items, this study identified that 54% of the root cause for out-of-stocks can be attributed to store personnel unaware of the potential out-of-stock, and thus not making orders. This author emphasized that the timing of the last store order as the most critical component to reduce out-of-stocks. The solutions proposed were to enhance store order quality, strengthen merchandise planning and execution, and have better alignment between the store replenishment cycles with consumer demand.

Links to the current study

The majority of the current research seems under the impression that the major causes of out-of-stocks are store level execution issues. While this may be the case, there could certainly be other relationships to study and relate to out-of-stock issues. Generally, there seemed to be a lack of research to examine specific product/category characteristics as how they relate to on-shelf availability. With this in mind, my goal was to observe how visible characteristics of products and categories at the shelf can have an effect on an-shelf availability. Variables such as proper on-shelf placement, unit price, the number of planned facings, and the number of substitutes for a SKU are all examples of variables that could definitely have an effect on stockouts. Of course, one could argue that some of the variables included in the study (such as proper on-shelf placement) are certainly related to store execution, while some variables (unit price) are not. Simply put, the chosen direction for the study most certainly contains some elements which parallel previous studies, but it also contains elements which build on existing literature.

This approach has potential for strategic implications. For example, studying how the number of facings on the shelf for a particular SKU relates to the number of out-of-stocks can potentially have various implications for category management. This is likewise the case for studying many other shelf related characteristics, and their effects on their out-of-stock rates. In the following section, I will outline several hypotheses for the study and provide further description for variable selection.

Hypothesis Development

Naturally, the idea to gather data via photographing the retail shelf birthed several hypotheses based on what is observable from these photographs. For example, by observing the photographs and recording the prices of various SKU's (and their potential fluctuations), there is the potential to study the effects of price fluctuations on stockouts. There were a total of 6 hypotheses.

As shelf holding capacity decreases, the probability of a stockout occurring within a product category should increase (Stassen et al. 2002). To reverse this, as shelf holding capacity increases, the probability of a stockout occurring within a product category should decrease. Intuitively, a larger number of planned facings (increased shelf capacity and more likelihood of more inventory on the shelf) should decrease the probability of a stockout. This is in contrast to other SKU's that have a small number of facings. Furthermore, increasing facings can also increase OSA since fewer replenishments are needed to keep the SKU stocked at the shelf (Waller et al. 2010). Anderson Consulting (1996) also cited inadequate shelf capacities as a major driver of stockouts. For instance, if a store lacks the facings to even meet its daily demand, it could even be stocking out every day.

H1: The greater the number of planned facings for a product, the lower the probability of a stockout occurrence.

Generally, as prices for a product decrease, demand and market share for those products should increase (Waller et al. 2010). More consumers are able to buy cheaper products, and consequently, a larger volume of sales should be expected. In the case of items in a retail setting,

these products should show a higher velocity (more inventory turns), and thus a higher probability of a stockout.

H2: The greater the unit price for a product, the lower the probability of a stockout occurrence.

Anderson Consulting (1996) cited missing shelf tags as playing a role in stockouts. If a product lacks a shelf tag, the store managers will likely fail to order the SKU to re-stock the item. If a product is consistently improperly placed on the shelf via tag-SKU mismatches, this could be an indicator of how likely it will stockout. Furthermore, other studies show that store shelving is the root cause for stockouts 25% of the time (Gruen et al. 2002; Corsten et al. 2003). Of course, a product being improperly placed on the shelf may not simply be the fault of that store's execution. If a consumer picks a product up off of the shelf, and after reconsidering decides not to make a purchase, he/she may place the product back on the shelf in an improper place (where a different SKU belongs, for instance). In this case, there is a sense in which the SKU has stocked out because it is not properly placed on the shelf. However, in another sense, it has not stocked out; it has simply been misplaced. In further sections, the interpretations of these types of "exceptional" situations is outlined. In any case, the prediction made was that poor shelf placement should also indicate a lower OSA.

H3: The more accurate the shelf placement for a product, the lower probability of a stockout occurrence.

Waller and Stassen (2002) discuss the effect of stores carrying deeper assortments/substitutes. On one hand, they state that stores carrying deeper assortments have a higher likelihood of satisfying more consumers. On the other hand, they mention that a stockout occurring can be more likely as substitutes are added because of the decreased inventory holding capacity for each SKU. If a consumer has several substitutes to choose from, one might initially consider the chance of any one of those SKU's being out of stock to be quite small. However, as their shelf holding capacities decrease, their likelihood for stocking out should be greater. The implications could be slightly different for cross-brand versus same-brand substitutes, but in general, a greater number of substitutes should increase the probability of a stockout.

H4: The greater number of substitutes for a product, the higher the probability of a stockout occurrence.

Stassen and Waller (2002) state that if two items are highly substitutable and one of the items stocks out, a consumer should be likely to switch and purchase the substitute. If a SKU has stocked out, some of the consumer demand may transfer to a different substitute SKU, especially if that substitute has inventory on the shelf. In turn, this increase in demand for that substitute SKU should also increase the chance of that SKU stocking out. With this in mind, an additional variable worth considering is the number of other SKU's out of stock in the category, since this could also potentially predict it's stockouts. For example, consider the milk category. If SKU "Vitamin D milk" stocked out that day, perhaps this might have been caused by SKU "2% milk" or "1% milk" (both from the same category) stocking out, and the consumer choosing to purchase SKU "Vitamin D milk" instead. This could in turn cause SKU "Vitamin D milk" to

stockout. Because of this, the extra variable of “number of other SKU’s out-of-stock” was added for the analysis and an appropriate hypothesis added.

H5: As the number of other SKU’s in the category that are out-of-stock increases, the probability of a stockout occurrence increases.

Anderson Consulting (1996) reported an enormous out-of-stock rate of 11% on Sundays, and their findings were that Saturdays and Sundays were the busiest shopping days of the week. Because most of the shopping occurs on weekends as opposed to weekdays, one would expect stockouts to occur more often during the weekends. As more consumers are removing more products off of the shelves during the weekend, the chances of a stockout should be higher.

H6: There will be a higher probability of a stockout occurrence on the weekends.

Methodology

For my study, there were two basic components to the methodology. First, I ventured to a small retail store to take photographs of their shelves, in order to extract useful data from the photographs for analysis. Secondly, I analyzed the data for useful insights for my research.

Data Collection

I chose Wednesdays, Saturdays, and Sunday nights between 6 and 9 p.m. to take the photographs of the shelves. The original goal for the amount of data I intended to retrieve was 10 weeks. Because of some time constraints/unexpected limitations, I was only able to retrieve 8 weeks worth of data. This, however, was still enough data to draw a reasonable amount of conclusions.

The camera I used to take most of the photographs was a Samsung Digimax i6. On some occasions, I used an Iphone and a Canon Powershot a2200. Each night I went to take the photographs, I would start with bread, and then move to milk, before ending with taking the water’s photographs last. Throughout my data collection process, there were a total of 4 points within the store that I took photographs, since the refrigerated bottled water was located in 2 different parts of the store.

During this process, I discovered that there were some unexpected challenges in taking the photographs. First of all, I needed justification to the store manager as to why I needed to take photographs of the store. Fortunately, I was able to build some rapport with the store manager initially, and he was very tolerant of me. He was also very open with me about the replenishment processes of the categories, explaining that all 3 of the categories that I was studying were replenished via DSD (Direct-Store-Distribution). Also, he offered to provide extra replenishment information such as the shelf holding capacities. However, for the scope of my project, this information wasn’t necessary.

Secondly, because the store format was small, the layout was more cramped. The distance between the isles was quite short, leaving me less room to step back and take the photographs. Consequently, I needed to take multiple pictures of each shelf in order to fully capture all of the SKU’s in the categories. In some cases, this resulted with multiple photographs of the same shelf, which would later prove to add to the challenge of extracting the data from the photographs.

Data Extraction

Once the 8 weeks of data gathering was complete, the next phase of the process was to extract the data from the photographs. Each photograph needed to be carefully studied to extract figures for my chosen variables and information. The information that was extracted were the day (Wednesday, Saturday, or Sunday), Time of day, Category, Category Size, the total number of SKU's out of stock in the category for that day, SKU I.D, Stockout or not, number of units of inventory on the shelf, Unit price, price promotion, product promotion, proper on-shelf placement, planned facings, actual facings, number of same-brand substitutes, and the number of cross-brand substitutes.

To assist me, I was privileged to have the help of 3 MBA graduate assistants in extracting the data. With each photograph, they carefully entered the appropriate numbers for each variable within the observations. This was a long process that took approximately 4 weeks of their time. The general steps that they took when extracting the data can be found in Appendix A.

Once again, I was confronted with more unexpected challenges. Surprisingly, there were several variables that were open to interpretation as to how to accurately translate what was seen in the photos into actual figures to be recorded and used for data analysis. In some of the photographs, the products were placed so out of order that it was nearly impossible to decipher how many planned facings the store managers originally intended to have on the shelf. Another common discovery I had while studying the photos was that SKU's were repeatedly not being placed where their tags were located on the shelf. In this situation, I actually began to wonder if the store workers had intended to place those SKU's where their tags were not located. If this were the case, one could argue that those SKU's had indeed been placed properly on the shelf, simply because week in-week out they continued to be re-stocked at those locations. However, one could also argue that the product's location on the shelf didn't match the tag's location on the shelf, so the product was not properly placed on the shelf. Cases like the ones described above were situations that I first needed to admit to the possibility of multiple interpretations. More importantly, however, I needed to develop a consistent interpretation for purposes of data analysis.

Because there were three different individuals helping me to extract the data from the photos, an added complication was simply that I discovered each MBA student had had a slightly different interpretation for the "special cases" (described above) of interpreting the photographs. Again, my conclusion and my efforts at this point became mostly driven towards standardizing their interpretations so that the data could be as useful as possible. Fortunately, this was able to be done with relative ease.

Results

Once the data was extracted from the photographs, some descriptive statistics were done on the data, then a correlation table, and finally the regression test and analysis. An interesting note was that for all of the days that I had photographs for, none of the SKU's for water ever stocked out. The descriptive statistics for the data can be found in Table 1. Table 2 presents the correlation table. Fortunately, none of the variables showed a high level of correlation.

Table 1: Descriptive Statistics

Descriptive Statistics (n=665)

Variable	Obs	Mean	Std. Dev.	Min	Max
Stockout	665	0.098	0.297	0	1
Unit price	665	1.907	0.599	1	3.07
Proper on-shelf placement	665	0.669	0.471	0	1
Planned facings	665	4.435	3.098	1	12
Same-brand substitutes	665	4.713	2.604	0	8
Cross-brand substitutes	665	4.782	2.244	0	9
No. of other SKUs OOS (within category)	665	1.122	1.277	0	4
Milk category dummy*	665	0.465	0.499	0	1
Saturday	665	0.287	0.453	0	1
Sunday	665	0.337	0.473	0	1

*baseline category is bread

Table 2: Pairwise Correlation

Pairwise Correlation (n=665)

Pairwise correlations	Stockout	Unit price	Proper on-shelf placement	Planned facings	Same-brand substitutes	Cross-brand substitutes	No. of other SKUs (within category)	Milk category dummy*	Saturday	Sunday
	Stockout	Unit price	Proper on-shelf placement	Planned facings	Same-brand substitutes	Cross-brand substitutes	No. of other SKUs	Milk category	Saturday	Sunday
Stockout	0.190									
Unit price		0.190								
Proper on-shelf placement			0.190							
Planned facings				0.190						
Same-brand substitutes					0.190					
Cross-brand substitutes						0.190				
No. of other SKUs (within category)							0.190			
Milk category dummy*								0.190		
Saturday									0.190	
Sunday										0.190

Correlation coefficients printed in bold are sig. at p<10%.

Regression

For the regression test, a logistic regression was used (Table 3). This is used when the goal of the test is to be able to predict a dependent variable with a binary outcome. Because the purpose of the study is to find the drivers of stockouts (and the outcome being stockout or not), the logistic regression seemed a better fit for analysis as opposed to the ordinary least squares regression. The following sections address the hypotheses that were made initially. When recording the data from the photos, a stockout was notated with a “1,” and if a SKU was in-stock on the shelf it was notated with a “0.” Also, the variable “day of the week” (Wednesday, Saturday, and Sunday) was converted into dummy variables for the test. Thankfully, the R-squared value for the final model was .48. This was unexpectedly impressive, as nearly half of the variation in stockouts can be explained by the model. For such a small sample size (665), such a reasonable scale of predictability from the model was fortunate.

As the regression shows, an increased number of planned facings decreases the probability of a stockout, which affirms the hypothesis. We can know this at a 5% confidence interval since its p-value is .001, and its coefficient is -.69.

For the second hypothesis, the results were counterintuitive. With a p-value of .022, the model states that as unit price increases, stockouts also tend to increase. There may be some potential reasons why this could have been the case. First of all, perhaps the SKU’s with a higher price tended to have less shelf space, which could influence why they tended to stockout more regularly. Furthermore, if a store holds severely less inventory than needed for those higher priced SKU’s (as compared with lower priced SKU’s), it can again be more susceptible to a stockout. Secondly, higher priced items can be packaged in larger sizes with cheaper prices per ounce. This cheaper price per ounce could have spiked demand for these SKU’s, and therefore caused them to stockout more. A third potential explanation is that higher priced items are usually the brand products, as opposed to the private-label products. Consumers could have preferred the brand products over the private-label ones, causing the higher-priced brand products to stockout more often.

The more accurately placed on the shelf a SKU was, the less likely it would stockout. This was significant at the 99% level (p-value less than .000), which was very favorable. Of course, as previously noted, a different interpretation of the data could have potentially altered these results. Because I chose to record the SKU as a stockout if there was no inventory near the tag on the shelf, in some respects this was a more rigid interpretation. There were certainly cases when the SKU had inventory in a different spot on the shelf, with zero inventory in its proper spot.

In the case with the effect of substitutes on stockouts, the test showed that this variable was not significant (p-values of .433 and .324). There was not enough evidence in this case to suggest that the number of same-brand or cross brand substitutes have an effect on the probability of a stockout occurring.

Interestingly enough, the fifth hypothesis held true. As more other SKU’s stocked out, the chances of the SKU in question stocking out were higher. From a supply chain perspective, this can potentially shed light on how vendors for the retailer view stockouts. In other words, not only can stockouts of one SKU compel consumers to purchase a competitor’s product, but the competitor may also have inflated stockout data caused by another firm’s poor on-shelf availability.

Finally, the test was unable to confidently address the sixth hypothesis. The p-values for both Saturday and Sunday were .243 and .257, respectively. These, of course, did not meet the 90% confidence interval requirement.

Table 3: Empirical Results of Regression Analysis

Logistic regression	Number of obs			665	
	LR chi2(9)			206.02	
	Prob > chi2			0.000	
Log likelihood = -109.85498	Pseudo R2			0.484	
DV = Stockout	Coef.	Std. Err.	z		P>z
Constant	-2.48	1.84		-1.35	0.177
Unit price	1.37	0.60		2.28	0.022
Proper on-shelf placement	-5.27	1.04		-5.06	0.000
Planned facings	-0.69	0.22		-3.18	0.001
Same-brand substitutes	-0.14	0.17		-0.78	0.433
Cross-brand substitutes	0.16	0.16		0.99	0.324
No. of other SKUs OOS (within category)	0.38	0.15		2.54	0.011
Milk category dummy*	0.40	0.61		0.66	0.512
Saturday	-0.52	0.45		-1.17	0.243
Sunday	0.43	0.38		1.13	0.257
*baseline category is bread					

Conclusion

Ultimately, the main goal of the research was to make an attempt at trying to understand some causal relationships to stockouts using observable variables at the shelf level. In many respects, this objective was met. First of all, the logistic regression model had a relatively high coefficient of determination (R squared). Being able to run a regression analysis with such a high coefficient of determination from such a small sample size is quite rare. Secondly, four out of six of my original hypotheses were able to be addressed quite confidently. Of course one of those four yielded a counter intuitive result, but I am thankful that I was even able to address one of my hypotheses with confidence (let alone 4 of them).

The study inherently has its limitations. Especially as the project came to a close, I became increasingly aware of how large of a question the issue of on-shelf customer availability actually is. More specifically, the most obvious limitation is that the scope of the project was relatively small (only considering 3 categories from one store). Additionally, collaboration with the retail store and the suppliers for the study was limited.

Appendix A: Data Extraction Process

1. Finalize the product list to make sure the data collector will collect the information of the same SKUs
2. Fill in the day-of-week information
3. Make sure the number for the category size is equal to the number of total SKUs
4. The total number of SKUs out of stock in the category should be equal to the number of the SKU's in the category that stocked out
5. Record the name of the SKUs into the SKU ID column
6. Indicate whether there is a stock out for each SKU
7. Count how much inventory on shelf
8. Record the unit price of each SKU
9. Indicate whether there is a promotion for each SKU
10. Indicate whether the SKU on shelf is properly placed
11. Count how many planned facings of the SKU that should be on the shelf
12. Count how many actual facings of the SKU on the shelf
13. Count and record the number of same-brand substitute SKUs
14. Count and record the number of cross-brand substitute SKUs
15. Make sure the sum of the numbers of step 13 and 14 is equal to the total category size minus one.

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