Analyzing the Impact of Stock-Outs on Sales of Products in an Online Delivery Application

Chunfeng Wang, Marcelo Emilio Ghia Salazar Ante, Gaurav A B S

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1 Introduction

In recent years, the demand for online instant delivery services has surged, leading to significant innovation in inventory management and day-to-day operations. To meet customer expectations of instant delivery, online delivery applications have established Micro Fulfillment Centers (MFCs) as strategic logistical hubs. These centers allow for instant fulfillment of online orders, ensuring prompt and reliable delivery to customers' doorsteps.

However, maintaining optimal inventory levels at these MFCs is crucial to effectively meet customer demands. Stock-outs, which occur when an item is unavailable at an MFC, can have a significant impact on the sales and customer satisfaction of online delivery applications. Understanding the relationship between stock-outs and sales performance through rigorous data analysis is essential for decision-making and operational strategies. This research aims to assess the extent to which stock-outs affect the sales performance, providing valuable insights into effective inventory management and the implications of stock-outs on business operations.

The problem we aim to study is to analyze the impact of stock-outs on top-selling products sales in Micro Fulfillment Centers (MFCs) of an Online Delivery Application. As the application expands its business to include grocery delivery, efficient management of these MFCs becomes crucial for the company's success. To put a business framework on top of the analysis, we thought a simple decision making model to make give context to the results and show the importance of detecting the indirect impact that can produce the stockout of certain product into sales of others. The idea is to enable data-driven decisions regarding assortment, stock, promotions, and other factors, and understanding the value that specific products bring to the business is necessary.

In our analysis We identify top-selling products based on historical sales performance and study the impact of their out of stock on a select set of complementary products. By employing a regression model and examining the relationship between stock-outs, complementary products, and hourly sales, we provide valuable insights for data-driven decision-making and inventory management strategies.

2 Literature Review

The impact of stock-outs on the sales of other products has been a topic of extensive research, and several studies have shed light on this phenomenon from different angles. By examining the relationship between stock-outs and customer behavior, researchers have developed models and frameworks to provide insights for effective management strategies. One notable study by Musalem et al., (2010) focused on developing a structural demand model that captures the effect of out-of-stocks on customer choice. They recognized the need for a methodology that can handle slow-moving products, frequent stock-outs, and a large number of alternatives. Their approach involved simulating a time-varying set of available alternatives and estimating the impact of stock-outs on sales. By allowing for flexible substitution patterns based on utility maximization principles, their model provided a comprehensive understanding of the dynamics between stock-outs and customer preferences. Moreover, the researchers demonstrated how store managers could utilize the model to quantify lost sales caused by stock-outs and make informed decisions based on these insights. Expanding on the understanding of stock-out policies, Breugelman et al., (2006) investigated the impact of different stock-out policies on consumers' category purchase and choice decisions in the context of online grocery shopping. They explored three policies: immediate visibility of stock-outs without replacement suggestions, delayed visibility of stock-outs after purchase attempts, and immediate visibility of stock-outs with suggested replacement items. Through an online grocery shopping experiment, the researchers found that the adopted stock-out policy significantly influenced consumers' decisions. Making stock-outs not immediately visible created confusion and intensified the consumer's loss experience, leading to a reduced tendency to buy in the category. On the other hand, suggesting replacement items facilitated the substitution decision and slightly reduced the purchase cancellation rate. Interestingly, the effect of suggesting replacement items diminished when higher-priced, potentially suspicious items were recommended. These findings highlighted the importance of open and convenience-oriented stock-out policies for online grocery retailers. To provide a comprehensive understanding of consumer reactions to stock-outs, Campo et al., (2000) developed a conceptual framework that integrated the major determinants of consumer behavior in response to stock-outs. The framework accounted for product, consumer, and situational factors that contribute to stock-out losses. By empirically implementing the framework and collecting survey data, the researchers were able to determine the relevance of different factors and the direction and importance of their effects. This framework served as a valuable tool for retailers and manufacturers to quantify the impact of various factors on stock-out losses and make data-driven decisions to mitigate their negative consequences.

Considering the costs associated with stock-outs,Anderson et al., (2006) conducted a large-scale field test to measure the short- and long-term opportunity costs of stock-outs. Their findings confirmed that stock-outs not only had an adverse impact on other items in the current order but also affected future orders. These results emphasized the need to consider the long-term effects of stock-outs in inventory planning models to make optimal decisions. The researchers also incorporated their findings into a customer lifetime value model and explored different responses that firms can employ to mitigate the cost of stock-outs. Interestingly, their study revealed considerable variation in the effectiveness of different responses, indicating that offering discounts to encourage customers to back order rather than cancel their orders, which is commonly practiced, was the least profitable response among the ones evaluated. These insights had important implications for retailers seeking to improve their inventory management and reduce the negative impact of stock-outs. Examining the role of brand equity and the hedonic level of products, Sloot et al., (2005) investigated how these factors influenced consumer responses to stock-outs. They conducted a study involving Dutch consumers across various product groups and retail chains. The results indicated that consumers exhibited higher loyalty to high-equity brands compared to low-equity brands in stock-out situations. However, in hedonic product groups, consumers were more likely to switch to another store. Moreover, purchasers of high-equity brands in hedonic product groups were less inclined to postpone the purchase but were more likely to switch to another item within the same brand. The researchers also explored other variables such as stockpiling and impulse buying and discussed their effects on consumer behavior in stock-out situations. These findings highlighted the importance of considering brand equity and product characteristics when analyzing consumer reactions to stock-outs. In the realm of retail inventory management, Tan & Karabati (2013) addressed the problem of inventory optimization considering stock-out based dynamic demand substitution. They focused on retail settings with Poisson arrival processes, lost sales, and a fixed review period, order-up-to level system. The researchers presented a computational method to determine the order-up-to levels that maximize expected profit while considering profit margins, inventory holding costs, substitution costs, and service-level constraints. Given the complexity of calculating performance measures for multiple products, they proposed efficient and accurate approximations to compute the same measures. These approximations were then utilized in a genetic algorithm to solve the optimization problem. The findings demonstrated how retailers could increase their expected profits by incorporating substitution among different products and optimizing their inventory levels based on a comprehensive set of factors.

Collectively, these studies contribute to our understanding of how stock-outs impact the sales of other products. They highlight the importance of considering various factors, including customer behavior, brand equity, online stock-out policies, and inventory management strategies, to effectively address the negative consequences of stock-outs on overall business performance. By incorporating these insights into decision-making processes, retailers and managers can develop strategies to mitigate the adverse effects of stock-outs and optimize their operations.

3 Data

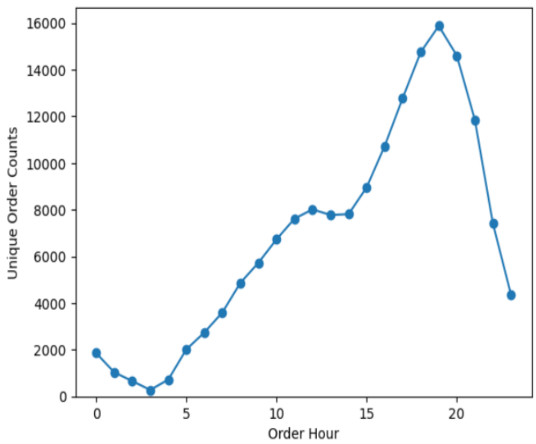
Our analysis is performed on data received from an Online Delivery Application and pertains to a particular Micro Fulfillment Centre (MFC) which has an inventory of 4363 products. There are two types of data sets, one containing the sales data and the other containing the stock-availability status of all products.

3.1 Sales data

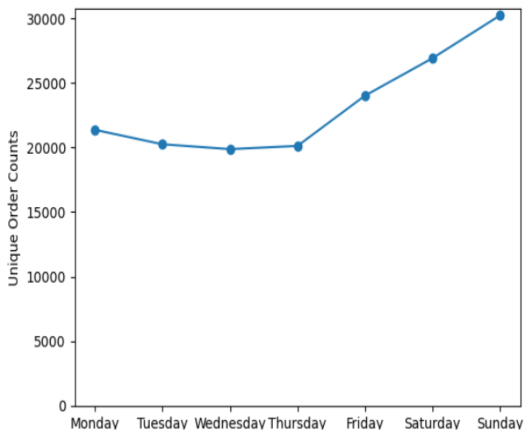
The sales data set contains the order level information of various features corresponding to all the orders placed on the application over a duration of 455 days, starting from '2022-01-01' uptill '2023-03-31'. The data set has information of 1,62,819 orders placed by 33,917 unique customers. The brief description of the features in the data set is as follows. A 'storeID' identifier representing the specific store from which the products were purchased. This information can be useful for analyzing store-level performance and understanding customer preferences for different stores. However since our data set is pertaining to a single MFC this feature is not relevant in our analysis. A unique 'customerID' identifier for each customer who placed the order. It could have enabled a customer-level analysis, such as understanding individual buying patterns and customer segmentation. However since 55% of customers ordered only once and overall 90% of customers have orders less than 10 times over the entire duration, such an analysis is not feasible. Other features include, a unique 'orderID' identifier for each order placed through the online delivery application, unique 'productID' identifier for each product included in an order, 'productName' providing the description of the product purchased and 'soldQuantity' which helps track the volume of products sold and enables sales analysis and inventory management. These features provide information about the specific items included in each order. Lastly, the 'orderDatetime' feature captures information of the date and time when the order was placed. It provides a more granular temporal aspect to the data, allowing for detailed time-based analysis, such as peak ordering hours or day-of-week patterns which can be seen in Figure 1. In figure (a) we see the variation in number of orders at a particular hour though out a day. The order frequency keep on increasing since the early hours and peaks during the late evening hours . In figure (b) we can see the variation of total number of orders by day of week and we find an expected increase towards the days corresponding to weekends peaking on Sunday. The weekends account of 35% of all the orders placed.

Figure 1: Time-based analysis: Hour-of-day and day-of-week patterns

(a) Distribution of Orders across hour of day



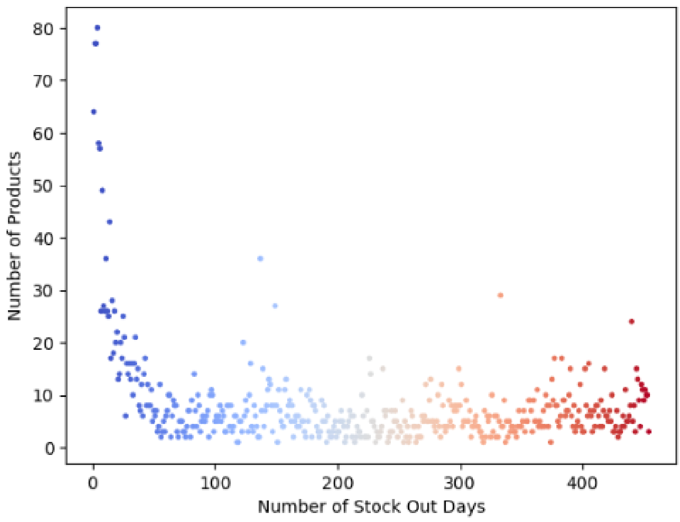
(b) Distribution of Order across day of week



3.2 Stock availability data

The stock-availability data set contains the daily inventory status for all the products, except for three products which are therefore not considered in the analysis. The inventory status is updated at midnight, recording True or False if the product is found to be available or not available in the inventory, on the particular date respectively. A total of 342 products did not have any day when the inventory status at end of day was recorded as out-of-stock, and a total of 377 products were never recorded to be in-stock. However, this has to be interpreted in the backdrop of the inventory status transition analysis, discussed later because in many instances a product which was not available at end of day might have been received in inventory during the following day and again sold out, resulting it being recorded again as out-of-stock at the end of day. Figure 2 provides a distribution of the number of products having certain number of stock out days. This figure is excluding the products having no stock out and also the products which were out of stock through out the entire duration of analysis. A total of 1,494 products (35% of all product) have stock out days less than 45 days (10% of the total duration), appearing on the left of the figure. On the higher side, a total of 1,794 (40% of all products) were out of stock for more than half the duration in analysis.

Figure 2: Distribution of stock out days



3.3 Stock-out duration

The stock-out duration is a critical aspect of the study. To define the logical rules for identifying the stock-out-start and the stock-out-end of each product, we have created two additional features in the availability data set, namely ‘datetime at start of day’ and ‘datetime at end of day’ which correspond to one second before midnight and one second after midnight, respectively to avoid any overlap of the interval. We also created the features ‘available at start of day’ and ‘available at end of day’, recording whether the product was available at start of day and at end of day. Product availability at end of day is known and the same is taken as the availability status at start of the following day. Only corresponding to the first date of the data set,‘2022-01-01’ we initialized the availability status at start of day as False if the product was out-of-stock at end of day and also was not sold on that day, otherwise we initialized as the value as True.

Further, to define the rules we investigated eight different types of stock availability transitions, depending on the availability status of the product at start and end of day and also considering whether the product was sold during the day or not. Table 1 illustrates the types of transitions and the corresponding number of such transitions.

Table 1: Product availability transition between start and end of day

Available at start of day	Sold during the day	Available at end of day	Number of transitions
F	F	F	797673
F	T	F	10480
F	F	T	8671
F	T	T	4816
T	F	F	1935
T	T	F	9550
T	F	T	784237
T	T	T	366438

For each product, we first identify stock-out-start, which is the timestamp at start of day if the availability status is False or the timestamp of the last order on a day at end of which the availability status is False. Once a stock-out-start has been identified, the stock out end is identified as the timestamp of the first order on any day or timestamp at end of day on a day when the availability status is True. Such a rule correctly accommodates for all types of stock availability transitions. When a product is sold during a day, correspondingly there is a first order timestamp and a last order timestamp, which is then used in determining the stock out duration.bbn

In all these transitions, a particular one pointed towards possible error in the stock evaluation data set. The scenario illustrated in the second row, wherein a product is not available at start of day and also at end of day but is sold during the day. This could be interpreted as a scenario where a product inventory was received during the day and was sold out again, which seems unlikely, however not impossible. Another plausible interpretation could be that the stock evaluation of the particular product was incorrect. Since there is no way to verify that the data is taken as it is, with the understanding that it occurs only 0.53% of the times, that is for 10,480 transitions out of a total of 1,983,800. In such a transition, product will be marked as being in stock between the timestamp of the first order and the last order of the day.

3.4 A measure of two products being complementary

Another essential aspect of the study is having a measure of complementary nature of two products, say product Y and product X. We capture this in the estimate of conditional probability of a product Y occurring together in an order, given product X is present in the order. To determine this, we consider all the orders which were placed when both products were in-stock and with in those orders the estimate of conditional probability is given as Number of orders containing both products Y and X, divided by the number of order containing product X.

Extending the idea, we create a ranking of potential complementary products of product X corresponding to all possible pairs by choosing different product Y. To focus on the most promising complementary products, we consider only the top ten in the ranking as complementary products of X. These products are expected to have a stronger association with X in customer orders, indicating that they are frequently purchased together.

4 Methodology

The Online Delivery Application presents a unique opportunity to examine the relationship between stock-outs of a chosen product (X) and the sales performance across a set of identified complementary products (Y). The objective of this study is to investigate the impact of stock-outs on the change of hourly sales and to understand the role of the complementary nature of products in this relationship.

When identifying, the products (X) whose stock-out would have maximum impact, we considered the following criteria. Chosen products shall be having high order frequency, identified based on the historical sales performance and also should have an adequate number of stock-out days to allow for a meaningful examination of the impact of stock-outs. Products with too few stock-out days may not provide sufficient variation for analysis, while those with excessive stock-out days may result in skewed effects. Therefore, we identify products (X) that strike a balance in terms of the number of stock-out days. Additionally, products (X) should exhibit a high average number of different products sold together in a single customer order. This criterion helps identify products that frequently co-occur with other items, indicating potential complementary relationships. By focusing on products (X) that are frequently purchased in conjunction with other products, we enhance the likelihood of capturing meaningful effects on the sales of complementary products (Y). Further, when selecting the set of products (Y), we analyze the conditional probability of two products occurring together in an order, as described in previous section to arrive at a set of products which can be deemed as complementary to product (X).

We decide to focus on the hourly sales because when stock-outs occur, they can vary in duration, ranging from a few hours to a few days. Unlike cumulative sales, which provide an aggregated view of sales over an extended period, focusing on hourly sales allows us to capture the immediate impact of stock-outs on customer behavior. By examining sales at this finer-grained level, we can gain insights into how customer behavior and sales performance are influenced by the occurrence of stock-outs within shorter time periods. For this purpose we analyze the stock out status of the product (X) as well on hourly basis. Comparing the stock out duration timestamps with the hourly timestamps, we determine the overlap, and if the overlap is above a certain cutoff value we mark that the product is out of stock in that hour.

Further to manage computational limitations, a data set narrowing strategy was employed. The initial data set consisted of 24 hours, 455 days, and 4363 products. To reduce the number of columns when incorporating fixed effects for products, two criteria were considered.Firstly, products with an average number of daily purchases greater than one were selected. This ensured that only products with consistent demand and meaningful sales volume were included in the analysis. Secondly, the data set was limited to the first six months of data, as stock-out occurrences primarily took place within this timeframe for the selected products. This allowed for a focused analysis of the impact of stock-outs on complementary product sales. By narrowing down the data set based on these criteria, the analysis was conducted while maintaining the integrity and relevance of the findings.

In our final analysis we employed a regression analysis to investigate the impact of stock-outs on complementary product sales. The methodology involved selecting a data set with criteria such as average daily purchases and a focus on the first six months of data. Complementary products were identified , and a regression model was constructed, considering log(hourly sales) as the dependent variable. The model included stock-out and complementary dummies, interaction terms, and fixed effects. To account for zero hourly sales, log(1+hourly sales) was used. By following this methodology, the study aimed to understand the relationship between stock-outs and complementary product sales while controlling for potential biases. Our model examines the get the percentage change of hourly sales as the dependent variable by taking logarithms and includes several independent variables representing stock-outs, complementary products, fixed effects, and error term. The regression equation is as follows:

$$\log(1+hourly\_sales_{p,t}) = \beta_0+\beta_1*stockout\_dum_t+\beta_2*comp\_dum_t+\beta_3*stockout\_dum_t*comp\_dum_t + \gamma\_m(t) + \theta\_dow(t) + \alpha\_h(t) + \sigma\_p(p) + \mu\_p,t(p,t) + \epsilon_{p,t}$$

where:

$\log(1 + hourly\_sales_{p,t})$ = Hourly sales of product p at hour t (in log)

$stockout\_dum_t = 1$ if X is out of stock at hour t, 0 otherwise

$comp\_dum_t = 1$ if p is a complementary product of X, 0 otherwise

$\gamma\_m(t)$ fixed effect of month

$\theta\_dow(t)$ fixed effect of day of week

$\alpha\_h(t)$ fixed effect of hour in the day

$\sigma\_p(p)$ fixed effect of product id

$\mu\_p, t(p,t)$ fixed effect of product-by-month

$\epsilon_{p,t}$ error term

As discussed before we determined the value of stock-out dummy variable based on the overlap between the occurrence of stock-outs and specific hourly intervals. We applied a pre-defined cut-off(greater than 0) value to classify hours as stock-out or non-stock-out periods.

We have also included 0 hourly sales for all products that have no recorded sales during specific hours. This allows us to account for the absence of sales during those hours and avoid potential errors in the logarithmic transformation. By utilizing log(1+hourly sales) as the dependent variable, we ensure a more accurate representation of the sales patterns and potential stock-out effects while mitigating the issues related to zero sales values.

5 Results

5.1 Regression Analysis Results

The table below shows the results of regressing the logarithm of hourly sales of Top 400 Sellers choosing X product being 3834 - Agua Bezoya 1.5L. We are interested the coefficient stockout_com_interaction, which is the interaction term capturing the effect of stockout and complementary product on Y.

Table 2: Model Comparison

Variable	Model without Fixed Effects	Model with Fixed Effects	Model with All Fixed Effects
stockout_dum	0.0073 (0.0012)***	-0.0015 (0.0011)	-0.0022 (0.0012)
com_dum	0.1184 (0.0020)***	-117042603.4502 (443410914.2873)	141997725.9534 (427146594.8403)
stockout_com_interaction	-0.0326 (0.0088)***	-0.0326 (0.0080)***	-0.0328 (0.0089)***
month	no	yes	yes
product	no	yes	yes
day_of_week	no	yes	yes
hour	no	yes	yes
product:month	no	no	yes
R^2	0.0020	0.1664	0.1791
No. Observations	1,733,256.0	1,733,256.0	861,840.0

The regression analysis results reveal important insights into the factors influencing log hourly sales. Firstly, the presence of a stockout, as indicated by the *stockout_dum* variable, is found to have a significant negative impact on sales. The estimated coefficient of -0.0015 suggests that a stockout is associated with a decrease in log hourly sales, meaning on average there is a 0.15% decrease in hourly sales when there is a stockout of product 3834. This implies that customers are less likely to purchase a product when it is experiencing a stockout situation. Additionally, the statistically significant standard error of 0.0011 strengthens the validity of the finding.

Additionally, the interaction between a stockout and being a complementary product is found to influence log hourly sales. The coefficient for the *stockout_com_interaction* term is -0.0326, indicating a negative relationship. This suggests that when a stockout occurs for a complementary product, the decrease in sales is amplified, on average by 3.26%. The statistically significant standard error of 0.0080 further supports this finding. The results demonstrate the importance of considering both stockouts and the complementary nature of products when analyzing sales performance.

Furthermore, the inclusion of fixed effects provides insights into the impact of specific factors on sales. The "yes" values for the month, product, day of the week, and hour fixed effects indicate that these factors have been considered in the model with fixed effects. This means that the analysis accounts for variations in sales patterns due to different months, products, days of the week, and hours. The R2 value of 0.1664 for the model with fixed effects indicates that approximately 16.64% of the variation in log hourly sales can be explained by the included variables and fixed effects. In contrast, the model without fixed effects, indicated by "no" values for the corresponding fixed effects, has a significantly lower R2 value of 0.0020, suggesting a weaker explanatory power. However, the fact that the coefficient for *stockout_com_interaction* remains unchanged with and without including fixed effects suggests that the relationship between stockouts, complementary products, and sales is not affected by the specific characteristics related to month, day of week, hour, and product. In other words, the effect of the interaction between stockouts and complementary products on sales is consistent across different months, days of the week, hours, and product types. Including these fixed effects in the regression analysis does not alter the relationship between stockouts, complementary products, and sales, indicating that these specific factors do not significantly influence the observed effects.

On the other hand, it is possible that the variable *com_dum* is highly correlated with the fixed effects related to specific products. As a result, when fixed effects are included in the model, the effect of *com_dum* gets absorbed by the fixed effects, leading to a higher coefficient value. It is important to note that despite the higher coefficient value, the lack of statistical significance suggests that the relationship between *com_dum* and log hourly sales may not be reliable or meaningful, as it is likely influenced by the presence of the fixed effects.

Finally, last thing to mention is that the more Y products marked as complementary, meaning more Y products have *com_dum* =1, but "less complementary" based on the co-ocurrence logic, the lower impact we see in the value of *stockout_com_interaction* and less significant too which make sense as the interaction between stockouts and complementary products becomes diluted or weakened. In other words, when "less complementary" products are selected based on co-occurrence patterns, the overall relationship between stockouts and sales is less influenced by the presence of complementary products. Consequently, the impact of *stockout_com_interaction* on sales diminishes and may no longer reach statistical significance.

5.2 Recommendations: next steps

Increase the sample size: We consider asking data from additional stores or locations to increase the sample size and to be able to try a different regression (Difference and Difference for example). In addition, expanding the time period of data collection to include more observations can further enhance the sample size, however, we had computational limitations to implement this. We were not able to grab more than a 6 months window period regressing with 400 products. Collaboration with other retailers or organizations to access their datasets and combine them with ours can also contribute to a larger and more diverse sample size but this is just very unlikely to achieve.

Conduct robustness checks: Perform additional robustness checks by employing alternative regression models or specifications. This can involve using different regression models to compare the results with our initial model. Test different specifications by including or excluding certain variables in the analysis.

Address endogeneity concerns: Investigate potential endogeneity issues by employing instrumental variable techniques or other econometric methods. This can involve identifying instrumental variables that are correlated with stockouts but not directly with sales, such as weather conditions or promotions, and using them to instrument for stockouts. Implementing a difference-in-differences approach by comparing sales before and after a stockout event can also help address endogeneity concerns, the problem is that in our approach we don't have treatment and control group, that is why we will probably need data from other store. Additionally, considering fixed effects models or controlling for unobserved factors that may be driving both stockouts and sales can strengthen the causal interpretation of the relationship between stockouts and sales.

Test for heterogeneity: Explore potential heterogeneity in the relationship between stockouts and sales across different product categories or customer segments. Conduct subgroup analyses to identify contextual variations and provide more targeted insights. This can involve analyzing the relationship between stockouts and sales separately for different product categories or product types. Conducting subgroup analyses based on customer segments, such as new customers versus returning customers or different demographic groups, can also help uncover heterogeneity in the effects of stockouts. To tackle this, we would need customer data.

Perform sensitivity analysis: Conduct sensitivity analyses by varying key assumptions or variables in the model. This can involve varying the thresholds used to define a stockout or complementarity between products and examining how different cutoff points affect the results. Assess the impact of excluding outliers or influential observations on the estimated coefficients. Analyze the robustness of the findings by considering different time windows or subsets of the data. Sensitivity analysis helps assess the stability of the results and the robustness of the conclusions under different scenarios.

Validate quantitatively with qualitative research: Gather qualitative data through interviews or surveys with customers or industry experts. This qualitative research can provide additional context and validation for the quantitative findings. Conducting interviews or focus groups with customers can help gather insights on their purchasing behaviors during stockouts and their perceptions of stockouts' impact on their decision-making process. Administering surveys can further capture customers' perceptions and opinions. Seeking input from industry experts or retail professionals through interviews or expert panels can also validate the observed relationships and provide additional insights.

5.3 Decision Making Analysis

Building a decision-making model based on the findings from the regression analysis can provide valuable insights for this Online Delivery Application business, and with this findings implement corrective actions in the supply chain. One crucial aspect is identifying complementary products, as customers often purchase them together, forming key product combinations. Understanding these complementary relationships enables the business to strategically manage its product assortment and offer, for example, targeted promotions, enhancing customer satisfaction and driving sales. The co-occurrence degree can provide hints to identify these relationships.

The regression analysis reveals that stock-outs of complementary products have a significant impact on sales, as indicated by the interaction coefficient. Higher positive values of the coefficient indicate a stronger negative effect of stock-outs on sales. This finding emphasizes the importance of effective stock-out management to minimize lost sales opportunities. As a very simple approach, with a Pareto analysis for example, Decision-makers can prioritize restocking complementary products with higher positive interaction coefficients to mitigate the negative impact of stock-outs and maintain sales performance. So tracking the direct effect of stockout of complementary products on Top Sellers sales and rank them according to this value could be a very useful way to tackle the problem and minimize the loss.

Inventory management plays a pivotal role in ensuring product availability and reducing stock-outs. With the knowledge gained from the regression analysis, decision-makers can make informed decisions regarding inventory levels for complementary products. They can optimize inventory replenishment processes and employ data-driven forecasting techniques, utilizing historical sales data to accurately predict demand. An accurate prediction of the demand and sales is crucial, to effectively determine the volume that was forecast but not sold because of complementary stockout and differentiate from other factors. Having reliable data on this volume can help to determine the real impact in terms of revenue of this stockouts. This data-driven approach empowers the Online Delivery Application business to efficiently manage inventory, minimize stock-outs, and sustain high sales performance.

6 Conclusion

The main purpose of the study is to investigate the effect on the sales of products in the event of a high selling product going out of stock within our Micro Fulfillment Centers (MFCs).

The regression analysis highlights several key findings regarding the relationship between stockouts, complementary products, and hourly sales performance. Firstly, the presence of stockouts has a significant negative impact on sales, resulting in a decrease in hourly sales for the analyzed product. This suggests that customers are less likely to make a purchase when the product is out of stock. Additionally, the interaction between stockouts and complementary products further amplifies the decline in sales. When a stockout occurs for a complementary product, the decrease in sales is magnified, indicating the interdependency between these factors.

Incorporating the insights from this analysis into our supply chain and operational strategies will enable us to minimize stock-outs, enhance customer satisfaction, and sustain high sales performance. By effectively managing inventory and understanding the impact of stockouts on complementary products, we can implement corrective actions and make data-driven decisions that contribute to the growth and success of our grocery delivery business.

We also acknowledge the limitations faced during the study and have proposed ways to improve under the recommendations section. Since the study is pertaining to an online application, they could be a variety of data like, customer's search or click data, available from the platform which could broaden the scope of the study and also could benefit from customer behaviour analysis.

7 References

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