Forecasting Model for Sporadic Distributor-Based Market

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ABSTRACT

With the evolution of technology, more data became available to observe consumer purchase patterns. Traditional forecast methods used to rely on only shipment history. Nonetheless, due to the accessibility of consumer data, a forecast process that integrates downstream flow has shown good results in improving the forecast accuracy in supply chains. In this research we investigate the benefits and validity of linking downstream distributor data in a fast-moving consumer goods company to improve forecast accuracy for intermittent demand. We used multi-tier regression analysis to link distributor sellout data to a retailer in order to predict shipment volume, and then performed a comparison analysis using the Croston method. We concluded that using multi-tier regression analysis has made a slight improvement on an aggregated level; however, the success of this method is subject to data availability that could be a constraint in certain situations. The Croston method has shown significant improvements at the item level and helped to better stabilize the forecast, yet it doesn't consider downstream data. We show a comparison between the two methods, and how to primarily link distributor data in the company's forecast to improve forecast accuracy.

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1 INTRODUCTION

1.1 Background

Inaccurate demand forecasting impacts a company's business and operation in several ways. Generally, if the company forecasts demand higher than the actual demand, it will lead to higher inventory cost and failure in capacity management, causing the company's profitability to decrease. On the other hand, if the forecasts are lower than the actual demand, the situation will cause longer delivery time and more stockouts, which will eventually lead to missed revenue opportunities and, more severely, a loss of customers (Suryapranata, 2003). In more extreme cases, inaccurate forecasting could even affect the survival of a company, as seen in the case of an aircraft manufacturer that went bankrupt because the company failed to manage the customer distress caused by overbookings (Prokesch, 1986).

Therefore, many companies, regardless of the industry, have put effort into improving their demand forecasting. A well-known fast moving consumer goods (FMCG) company and Fortune 500 company, which is the sponsor of the project, is also putting effort into improving its forecasting method through analyzing its shipment history and applying moving average to the forecast model.

1.2 Problem Statement

However, regardless of the forecasting effort, the sponsor company is experiencing low accuracy in its forecasting model in the Region A. It has many over-shipping and under-shipping circumstances (see Figure 1). The actual shipment volume is sometimes five times higher than the forecast, leading to stockouts. Conversely, it also suffers from the situation where actual shipment is 20% of the forecasted demand. The leader of the company states that the problem is caused by sporadic demand from the distributors.

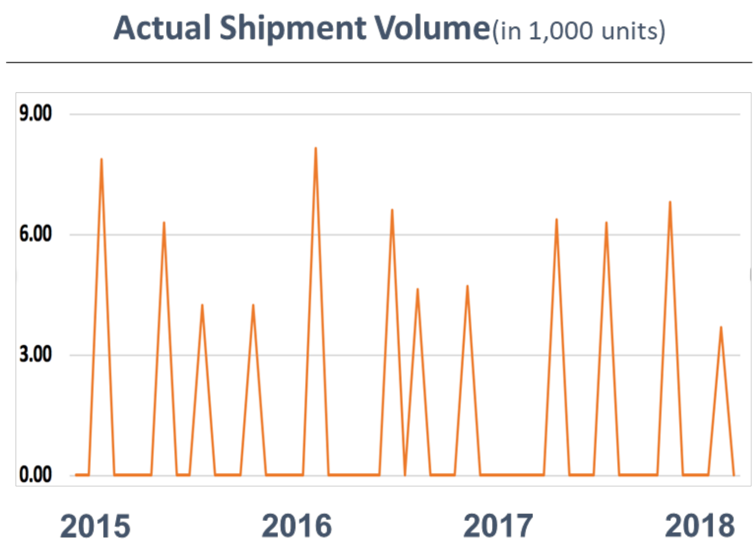
Top 5 over-shipping		
Actual shipment vs Forecasting	**Shipment (K Unit)**	**Forecasting (K Unit)**
487%	4723	970
331%	2026	612
272%	4804	1764
260%	2926	1125
251%	1972	786
Top 5 under-shipping		
Actual shipment vs Forecasting	**Shipment (K Unit)**	**Forecasting (K Unit)**
20%	2815	14007
27%	1883	6861
41%	2036	4909
49%	6733	13792
53%	3709	7013

[Figure 1: Top 5 errors between actual shipment and forecasting. Data from the sponsor company]

1.3 What is Sporadic Demand?

Sporadic demand (also known as intermittent demand) is often characterized by two factors. First, the demand pattern shows several periods with zero demand. Second, when the demand occurs, it is highly variable. Therefore, the pattern usually occurs in a product when it is at the end of the cycle or where it is in the off-seasonal cycle. For example, the spare parts industry is well known for its sporadic demand. Spare parts for aviation and defense industry are kept in stock, but those parts usually have zero demand over a period of time because customers only order when they require maintenance or have to repair the products (Waller, 2015).

The sponsor company is also facing highly sporadic demand. If we look at the actual shipment volume of a single SKU (Stock keeping unit), we could easily identify that sporadic demand occurs over time. The shipment volumes have lots of periods of zero demand, and even when there is a demand, it is highly fluctuating, ranging from 3,000 units to 8,000 units (see Figure 2). Therefore, with the current forecasting model that the company utilizes, it was not able to accurately capture the sporadic demand and forecast the demand accurately.



[Figure 2: Sporadic demand of the company. Data from the sponsor company]

1.4 Objective

In this research project, we analyze factors that drive the sporadic demand in order to improve the company's current forecasting method. We link those identified drivers into the forecasting model by transitioning the causal relations into a mathematical model. The Capstone project addresses the real-world challenges of preventing high inventory costs or sales loss from the customers and proposes a solution that could alleviate those challenges.

2 Literature Review

This project aims to improve the forecast accuracy by building up a forecast model for the sponsor company struggling with sporadic demand issue. Therefore, we conducted a literature review related to various types of forecasting approaches in order to seek an appropriate method. A brief for both traditional methods and specific forecasting methods for sporadic demand is placed as follows

2.1 Traditional Forecasting Methods

The traditional forecasting methods include naïve, cumulative and moving average approaches. The naïve forecasting method puts weight on the most recent observation, and the cumulative and moving average forecasting methods put equal weighting on all observations. These forecasting methods equally treat the data without having different rates or weights (Spyros, Wheelwright, & Hyndman, 1998).

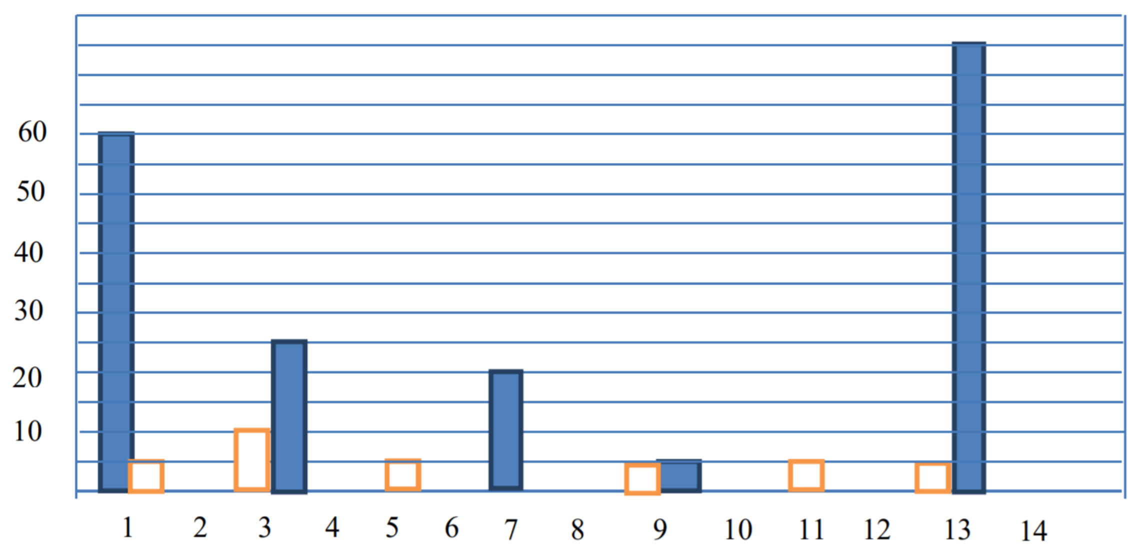
However, in most situations, the value of data degrades over time and newer observations tend to be more accurate than older observations. To address these circumstances, exponential smoothing models have been introduced (Brown, 1956).

The exponential smoothing method has been advanced by considering the trend of the data (Holt, 1957). A simple exponential smoothing model only captures the stationary level, thereby always lagging a trend of the actual data. The Holt Model captures the trend factor through introducing “Beta” (β) constants to the model. It estimates the new trend and old trend and weighs that information to provide an accurate and non-lagging forecast.

Much effort has been put into the Holt model and seasonality was included in the model (Holt, Winter, 1960). Many products in real life have seasonality. For example, chocolate and candy are mostly sold in early February for Valentine's Day. These seasonality factors of the products were considered in the Winter-Holt model as seasonality smoothing factor.

2.2 Forecasting Methods for Sporadic Demand

Traditional forecasting methods are very useful in most cases, since they capture level, trend, and seasonality when forecasting demand. However, there are difficulties with traditional forecasting methods when forecasting sporadic demand (Oguji, 2013). Moving average and exponential smoothing methods forecast demand based on the most recent observation. But since the sporadic demand demonstrates zero demand in several periods (see Figure 3), these traditional methods lead to a poor forecast.



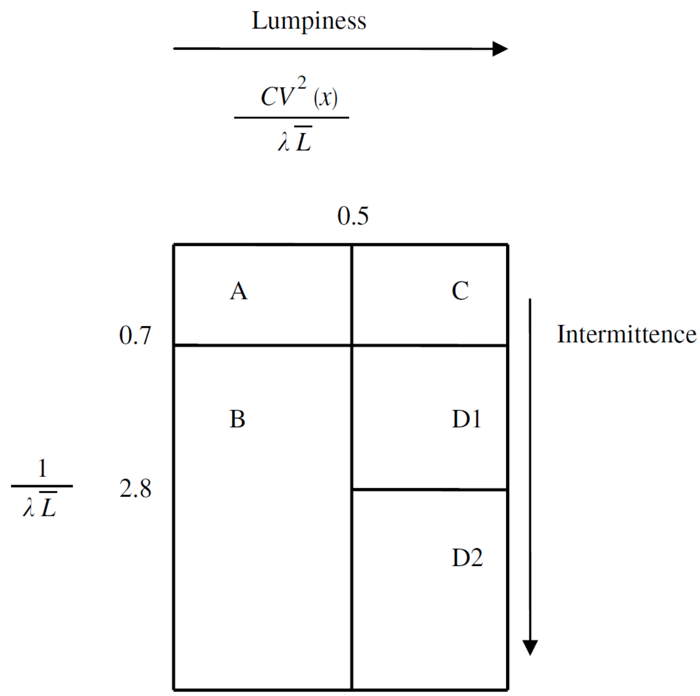
[Figure 3: Example of Sporadic Demand Pattern (Oguji, 2013). Sporadic demand is characterized by zero demand and high volatility in demand. Blue and white bars represent different items with sporadic demand patterns.]

Croston's method provides more accurate outcomes when demand shows multiple zero demand (Croston, 1972). It takes into account both demand size and interval time between demands by separating the data into two components – non-zero demand time series and inter-demand interval time series which is the timeframe between demand occurrences. Through considering the two factors, the model estimates the average demand per time period.

Several variations were introduced in order to improve Croston's method. Syntetos and Boylan (2001) showed that Croston's estimator is biased to over-forecast and proposed a modification to exclude the bias through presenting a correction factor of (1- α /2), where α is the smoothing constant (Syntetos & Boylan, 2005). Shale, Boylan and Johnston (2006) specified correction factor of [1-(α/(2- α)] to remove bias in Croston's model.

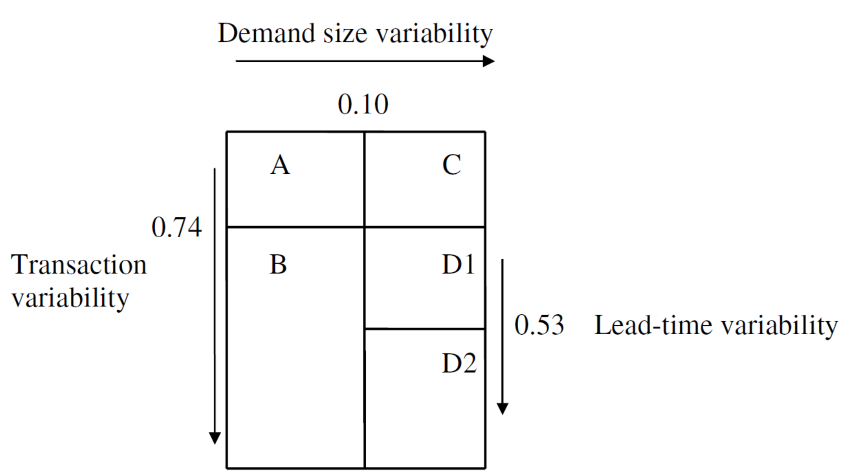
2.3 Categorization schemes

As various forecasting methods have been presented, multiple categorization methods have also been introduced in order to select the most appropriate estimation procedure within each category. The Williams methods categorize the demand patterns based on lumpiness and intermittence of the demand (Williams, 1984). Lumpiness is defined as having both intermittent and erratic characteristics, and it is indicated by coefficient variance, mean demand arrival rate and mean lead time duration. In the matrix below, the D1 and D2 segments are highly lumpy, whereas the A segment is smooth and stable (see Figure 4).



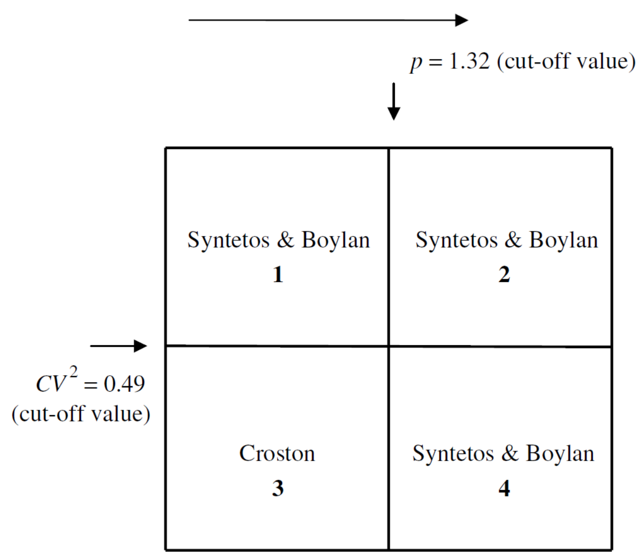
[Figure 4: Williams' Categorization Scheme. Stock control with sporadic and slow moving demand (1984). J Opl Res Soc 35: 939–948]

Eaves claims that Williams' scheme does not adequately describe the demand structure where smooth demand patterns exist, and proposes a new categorization scheme, which considers demand size variability, transaction variability and lead-time variability (Eaves, 2002) (see Figure 5).



[Figure 5: Eaves' Categorization Scheme. Forecasting for the ordering and stock holding of consumable spare parts. PhD thesis (2002). Lancaster University, UK.]

However, Syntetos, Boylan and Croston improve Williams' categorization scheme because Eaves' scheme was restricted to certain situations . The scheme considers the variability represented by coefficient of variation (CV) and the inter-demand interval represented by *p* value (see Figure 6). It claims that Croston's method is more applicable to fast moving items with low variability and the Syntetos & Boylan method should be used for the opposite categories.



[Figure 6: Syntetos, Boylan and Croston's Method. On the categorization of demand patterns. Journal of the Operational Research Society (2005) 56, 495–503]

2.4 Multi-tiered causal analysis

In addition to time series analysis as a forecasting method that is commonly used when product is in maturity phase or in steady phase, is regression analysis (Chambers, Mullick, Smith, 1971). Multi-tier regression analysis is not really a technique but rather a procedure or process that models the push/pull effects of the supply chain by linking a series of multiple regression models together (Chase, 2013). This procedure uses information from downstream data such as point-of-sale transaction, product location in the store, and other information that shapes consumer demand. Then once demand is predicted another model is built in conjunction with some other variables to be able to predict the shipments. For example, if we want to build a model that predicts the number of shipments for a certain product, then we would first predict the demand (Chase, 2013), and use the predicted demand as an independent variable to predict number of shipments as shown in the following equation(Chase, 2013).

$$(1)\ Demand\ (D) = \beta 0\ Constant + \beta 1\ Trend + \beta 2\ Seasonality + \beta 3\ Price + \beta 4\ Advertising + \beta 5\ Sales + \beta 6\ \%\ ACV\ Feature + \beta 7\ FSI + \beta 8\ Store\ Distribution + \beta 9\ Competitive\ Price + \cdots \beta n$$

Then we use the predicted demand as an independent variable to predict the number of shipments:

$$(2)\ Supply\ (S) = \beta 0\ Constant + \beta 1\ D(lag 1 - n) + \beta 2\ Trend + \beta 3\ Seasonality + \beta 4\ Gross\ Dealer\ Price + \beta 5\ Factory\ Rebates + \beta 6\ Cash\ Discount + \beta 7\ Coop\ Advertising + \beta 8\ Trade\ Promotions + \ldots \beta n$$

This procedure requires data to be available across the supply chain, which is not the case in every environment. We used this approach to link downstream data of the distributor to predict the number of shipments in a given month. However, usually the demand doesn't affect shipment volume in the same month the demand occurs; instead, that impact will be lagged across n number of time periods. For example, if demand increases in this time period, number of shipments will increase in the following time period. For example, mass merchandisers, such as Wal-Mart, buy in bulk prior to high periods of consumer demand, usually one or more periods (months or weeks) prior to the sales promotion (Chase, 2013). The key success factor of this method is to have enough explanatory variables that will be significant in building the model. We used Chase (2013) as a reference, as the main objective was to link downstream data in order to predict number of shipments.

3 Methodology

Based on the various types of forecasting method that we reviewed, we will present the methodology that we use. We would explain about the data that were acquired, the metrics that were used to compare the forecasting accuracy, and the approaches such as Croston and regression analysis.

Through the literature review, we have covered various forecasting methods. All these methods provide a basic understanding of how to improve forecasting models of sporadic demand. However, to systematically approach the current problem, we will take two approaches. The first is to use a multi-tier regression analysis. The second approach is to directly forecast the sporadic demand by applying the intermittent forecasting method (Croston). These methods will be compared and evaluated through metrics such as A-MAPE (Mean Absolute Percent Error), root mean square error (RMSE), and mean deviation (MD).

Also, the categorization method proposed by Syntetos, Boylan, and Croston (2001) could be utilized since our forecasting methods include various SKUs with different behaviors. That is, we will categorize the SKUs into meaningful categories with similar characteristics and apply different forecasting methods to enhance accuracy and exclude bias.

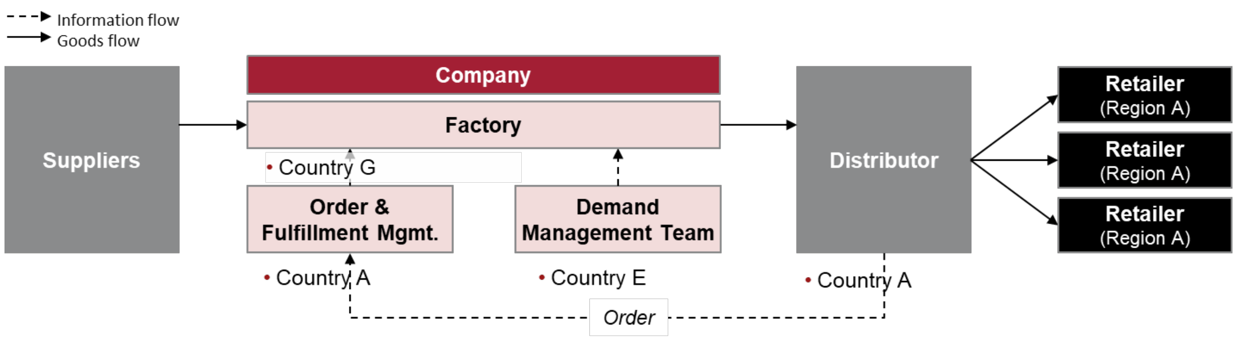
$$\mathrm{RMSE} = (\tfrac{1}{n}\textstyle\sum_{t=1}^{n} \quad (Y_t - F_t))^{1/2}$$

$$\text{A-MAPE} \;= \frac{\frac{1}{n}\sum_{t=1}^{n} \quad |Y_t - F_t|}{\frac{1}{n}\sum_{t=1}^{n} \quad Y_t}$$

$$M\mathrm{D} = \textstyle\sum_{t=1}^{n} \quad \frac{et}{n}$$

3.1 Scope

A leading FMCG company operates the business in different regions and our focus is Region A. In the case examined for this research, a distributor, which has a direct relationship with retailers in various regions, places orders through a fulfillment management team in Country D. Then, Country D team will manage the orders from distributors and deliver the information to the factories in Europe. Receiving materials from suppliers of many countries, the factory fulfills the order to the distributor in Country A. In the process, Demand Management team located in Country E forecasts shipments based on historical shipment data to analyze the available capacity and to provide forecasts to fulfillment management team (see Figure 7). Even though the company has set up firm process across the countries, due to the sporadic demand we believe there is a huge opportunity for improvements.



[Figure 7. Overall process of information and goods from suppliers to retailers. Data from the sponsor company]

In this research project, we mainly focus on improving the forecasting accuracy, which will lead to optimized cash flow and ensure product availability at the time when customers need it. We analyze what behavior drives this sporadic demand and how the company can improve the current forecasting method by linking the information between the company and the distributor.

3.2 Data Acquisition and Pre-processing

As a first step, we have gathered relevant data from the sponsor company (See Figure 8).

Data type	Timeline	Type
Shipments Data	2015.10 ~ 2018.10	Weekly / Monthly
Forecast Data	2017.02 ~ 2020.09	Weekly / Monthly
Inventory Data	2015.10 ~ 2018.10	Monthly
Sellout Data	2015.11 ~ 2018.10	Monthly

[Figure 8. Acquired Data Sets. Data from the sponsor company]

Even though the analysis requires more data points, we first considered the basic data set.

i) Shipments data represents the actual shipment volume for each SKU that was sent from the company to various distributors. The data was defined weekly and monthly, as the system of the company was not able to gather data at a more detailed level.

ii) Forecast data that includes forecasted volume for each item was analyzed by the company. This data will be the starting point to develop the forecasting method and later it will be used to compare various metrics such as RMSE (Root Mean Square Error) or A-MAPE (Adjusted Mean Absolute Percent Error) with developed model.

iii) Inventory data represents end of month inventory balance at the distributor. Due to the system's limitation, it was only received as monthly figures. Through analyzing the inventory data, we could examine the stock-outs and how those events could impact the sales and shipments of the company.

iv) Sellout data represents the material flow that was sent from distributors to the retailers. The data was gathered to understand the behavior of distributor market, as the demand from retail side continuously affects the volume of distributors' shipments.

Next, we preprocessed the data using R (a statistical analysis tool) into a form that is more easily analyzed. For example, the date was sorted in a wide format where each month was in a different column, which was not the right format for building regression model. Therefore, we revised the data into more applicable format by rearranging the multiple date columns into one column. Also there are "N/A"s in the raw data, which had to be either eliminated or replaced with a substitute value. After discussing with the company, we decided to change "N/A" to 0 value for some items, and to totally exclude from the study for other items.

3.3 Analysis of Current Forecasting Method

Analysis of current forecasting method is conducted using the following metrics to measure accuracy and bias. Since the demand is sporadic and there is a lot of zeros, mean absolute percent error, which is a common measure, would not be applicable, as it is not possible to divide by zero. Hence, we used root mean square error (RMSE), and examined the A-MAPE (Alternative Mean Absolute Percent Error) introduced by Hoover (Hoover, 2006).

Second aspect is to capture forecast bias, which represents the tendency to over- or under-predict. Then Mean Deviation (MD) was examined to capture bias.

3.4 Development of New Forecasting Method

3.4.1 Croston method and its extensions:

Traditional forecasting methods such as moving average, time-series or exponential smoothing have flaws when forecasting intermittent data. For example, moving average forecast is based on most recent observation even though intermittent demand does not have recent observation.

There are various forecasting methods for sporadic demand in research field. Among those, the most basic approach and a good starting point would be the Croston model (Croston, 1972). It separates the data into two categories: non-zero demand and inter-demand interval time series. Through identifying those categories, it will estimate the average demand per time period.

There are also many models that derived from Croston's model. One variation is eliminating the bias of the Croston's model (Syntetos, Boylan, 1999). These methods could also be used in multiple situations, and since we segmented into different groups, we could apply it to different segment groups.

3.4.2 Multi-tiered regression analysis

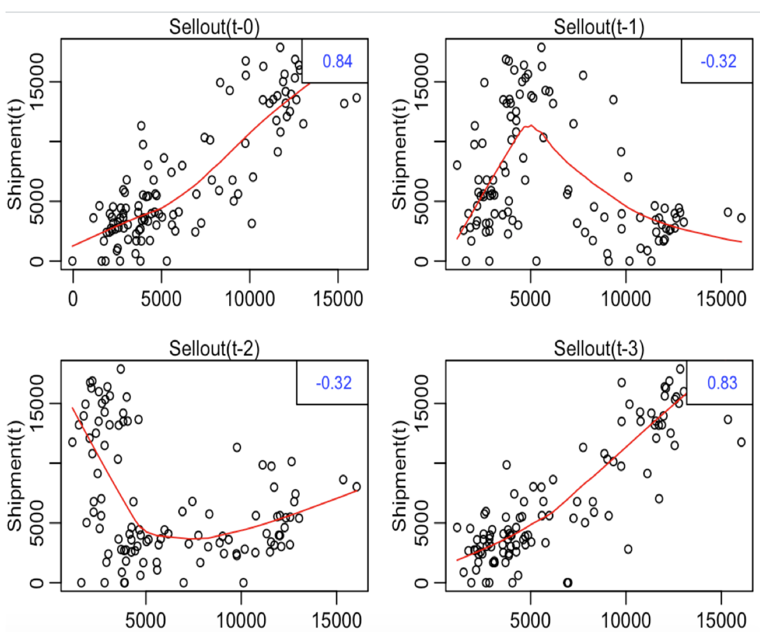
To build the multi-tiered regression analysis model, we requested several data points, such as distributor sellout, inventory, promotions, rebates, promotions, and special events (See Figure 9).

Category	Data Point	Notes
Sales	Special events	National events (ex. Ramadan)
	Sales Target	Target set by sales team
	Sales Promotion	Various sales promotions (ex. 1+1, 50% D/C)
Supply Chain	Customer Fill Rate	Satisfied orders / requested orders
	Inventory in-transit	Inventory transferring from factory to distributor
Others	Price	Not available
	POS data	Not available
	Trade promotion	Not available
	Competition Prices	Not available
	Premium Displays	Not available

[Figure 9. Data to be included for multi-tier regression analysis]

We were able to obtain sellout data and promotions, and we extracted information about major events from the internet. The other data points were not available as the company did not track the data such as competitors' prices. Also, data such as point of sale (POS) data are sensitive to retailers, so the data could not be provided.

Data were available in three levels: 1) Brand; 2) Category; and 3) SKU. We agreed to make the model on the category level as it will produce a simple model with fewer independent variables, then split the resulting forecast on each item with respect to how much it contributes to the forecasted demand. After the data were preprocessed as mentioned in Section 3.2, we started to investigate the demand lag effect on the data by lagging sellout data and validating the correlation between a number of shipments and demand in each period. Since sellout data was already lagged by one month, the correlation is the highest in t-0 (time interval 0 without in lag), as shown in Figure 10. After investigating the lag, we started adding other explanatory variables such as seasonality, promotion, and consumer price index. Through stepwise regression, we removed variables that are not significant in the model and validate R2 (R-squared or a statistical measure to determine the correlation). Once we reached a model with highest R2, we predicted the demand and measured its accuracy through A-MAPE, RMSE and MD to decide whether or not this approach is feasible in this scenario given the limited data points.



[Figure 10: Lag plot between shipment and sellout]

Once the forecasting approach is selected, we will have different data set for training and testing. The data will be split 80/20 where the first 80% of the data will be used for training and 20% of the data will be used for testing. The purpose of not utilizing 100% of the data is to prevent overfitting of forecasting method and to validate the model with fresh or never-used data. Overfitting might explain the past data better, but it would not be able to forecast accurately. Therefore, the test data set would never be used for training data.

We will use A-MAPE, RMSE and MD metrics to test the developed forecasting method to provide comparison with the initial forecasting method. By comparing with the initial forecasting, we would able to see how much it improved in terms of accuracy and bias.

4. Results and Analysis

In this section, we discuss the results obtained from conducting simulation, regression analysis by category and brand, and Croston method. We will compare the forecasting accuracy of our analysis with internal analysis that the company has conducted.

4.1. Results

4.1.1. Simulation based on target inventory

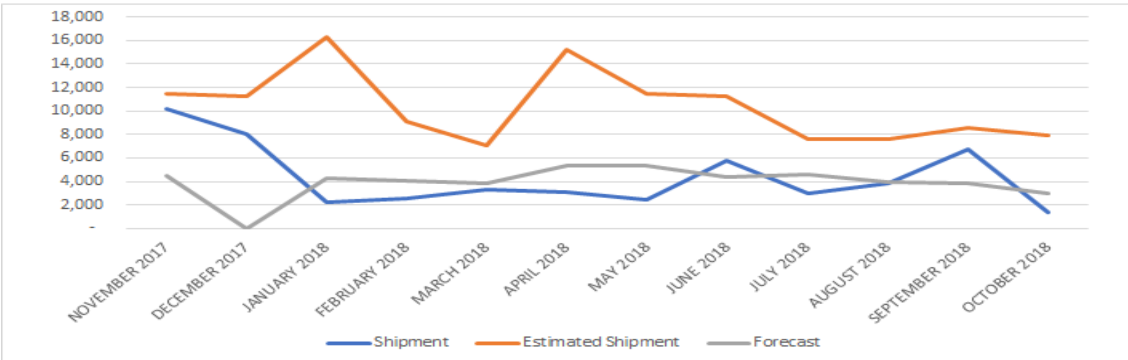
We developed a simulation experiment to compare the result with the internal forecast. As we initially assumed that the company will replenish the products that fall below the target inventory level, we conducted the simulation to verify this behavior. The target inventory level was calculated by the average of inventory level for the past one year (in SKU level). Then we estimated the shipment volumes by using the below equation:

Estimated Shipment = Target Inventory – (Last Month Ending Inventory – Sell-out)

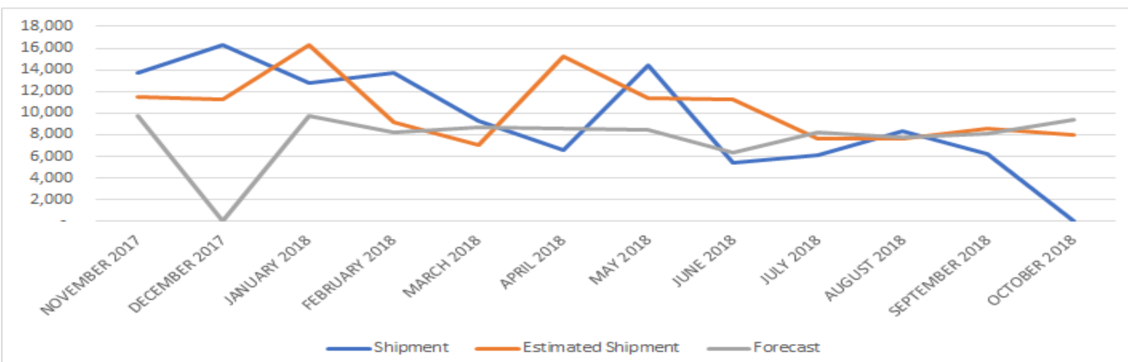
That is, if the last month inventory minus sellout falls under the target inventory level, the company will replenish. If it does not fall below that level, the company will not replenish it.

Next, we aggregate (or sum up) the estimated shipment of the SKU to the brand level and compare the RMSE with the internal forecasting result (See Figure 11 and Table 01).

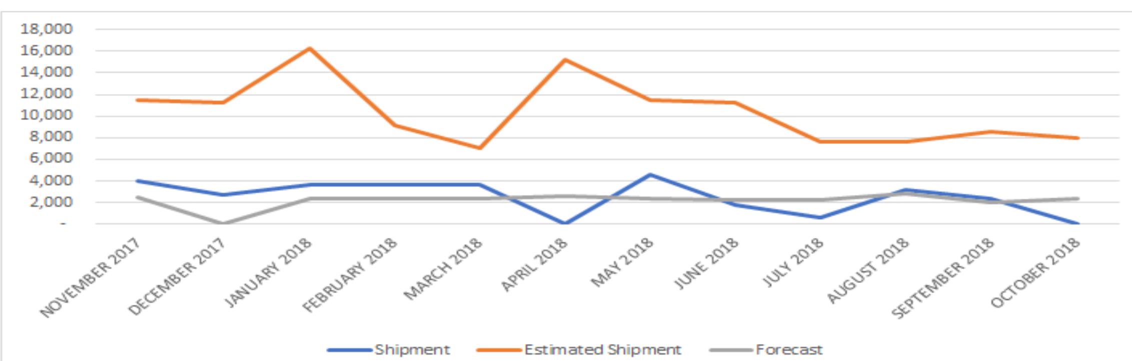
- Brand 1



- Brand 2



- Brand 3



[Figure 11. Simulation of shipments based on target inventory level]

[Table 01. Simulation results and forecasting accuracy comparison]

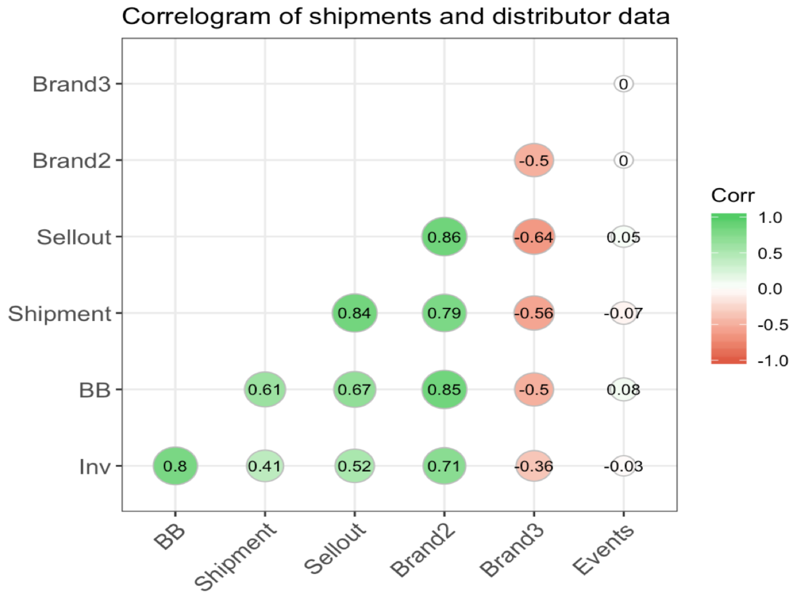
	RMSE_Simulation	RMSE_Internal	Improvement
Brand1	7,094	3,311	-53%
Brand2	4,644	6,176	33%
Brand3	8,523	1,701	-80%

Brand 2 had improved by 33% in terms of RMSE metric. However, the simulation accuracy was 53% and 80% less than the internal forecast.

4.1.2. Regression Analysis (Brand level)

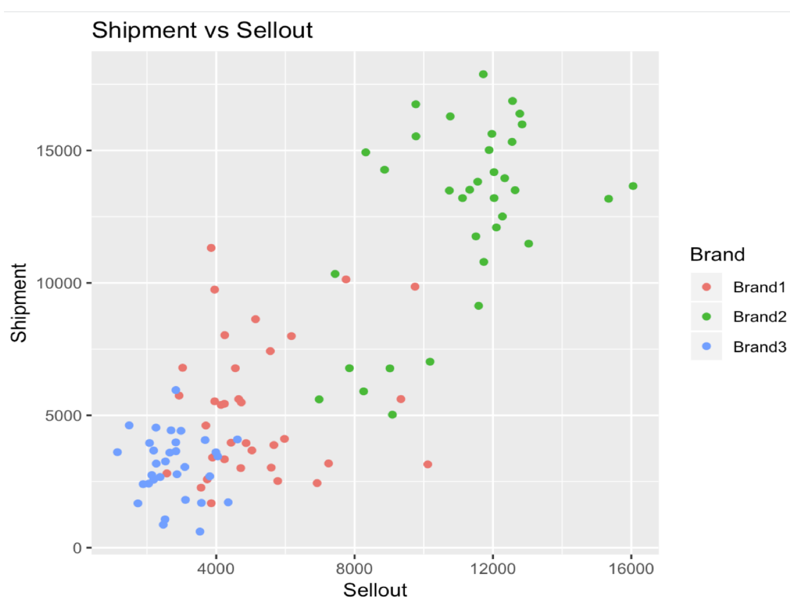
In order to conduct regression analysis on brand-level, we extracted the data on the brand-level. We were able to extract sellout, inventory level, distributor sales target (building block), customer fill-rate (CFR), orders, shipment, and forecast data. The timeframe that we used for regression analysis sections B, C, and D below is from October 2017 to September 2018. The reason for conducting analysis after October 2017 is that the company did not have the access to the inventory data before October 2017.

A. The underlying data in this part of the analysis includes three brands. Date range for this part of the analysis is between January 2016 and January 2019. Testing data is between January 2016 and October 2019, then we tested on the later time period. In this model we have shipment as the dependent variable, and Sellout, Inventory, building blocks (BB), and major promotional events (July and October) for the three brands. Before presenting the model, we investigated the correlation between shipment and other variables as shown in Figure 12.



[Figure 12: Correlation plot between shipments and distributor information]

We could see that sellout of the previous period (t-1) is the feature that is highly correlated with the shipment, and Brand 3 have a low correlation with number of shipments. To understand which item contributes the most to the volume shipments we plotted shipments against sellout on the training data set as shown in Figure 13, and as illustrated in the figure Brand 3 has the lowest volume across the three brands.

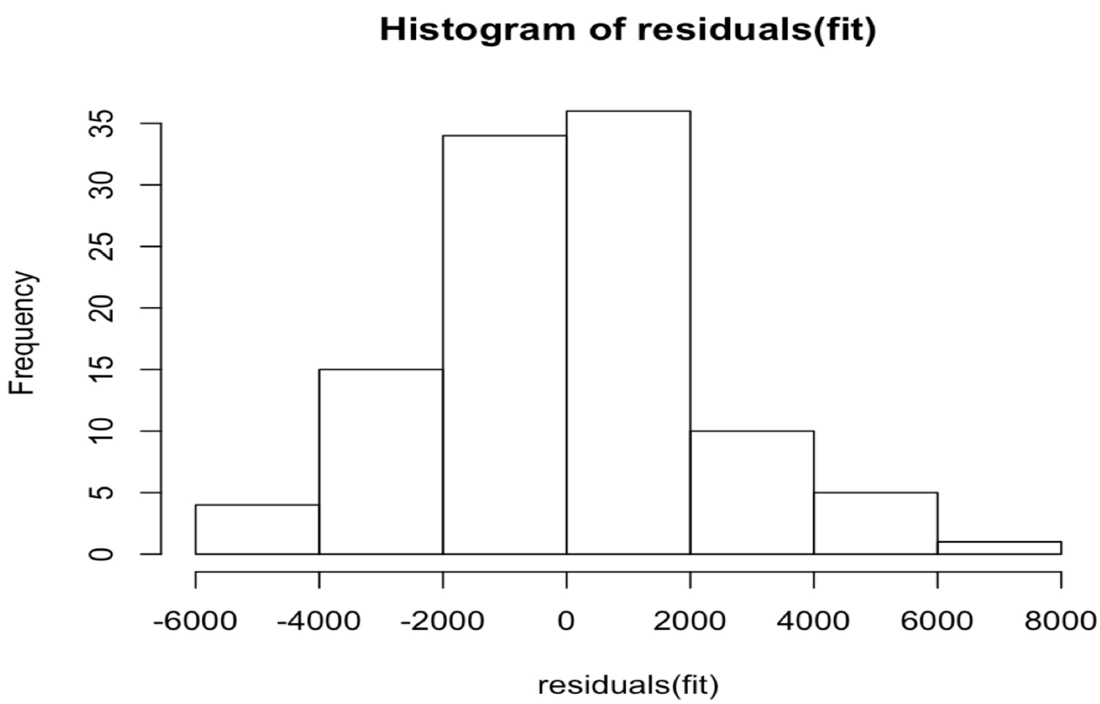


[Figure 13: scatter plot for shipment vs Sellout]

After that, we ran regression and the output model explained 77% of the variation with BB was insignificant with p-value 0.7. Then we removed building blocks and run the regression analysis again where the difference between R2 and adjusted r square has improved, and the model explained 78% of the variation. Inventory had a negative correlation as shipments from the manufacturing company increases when the distributor inventory level goes down, the equation of the model is

$$\begin{aligned} Shipment\ Volume \\ &= 4.984e + 03\ +\ 3.999e - 01\ *\ (Sellout)\ -\ 8.996e - 02\ *\ (Inventory) \\ &- 1.482e + 03\ *\ (Brand3)\ +\ 6.612e + 03\ *\ (Brand2)\ - 1.406e + 03 \\ &*\ (Promotional\ Events) \end{aligned}$$

The residuals of this model are normally distributed as shown in Figure 14, and the residuals vs fitted value was a random blob.

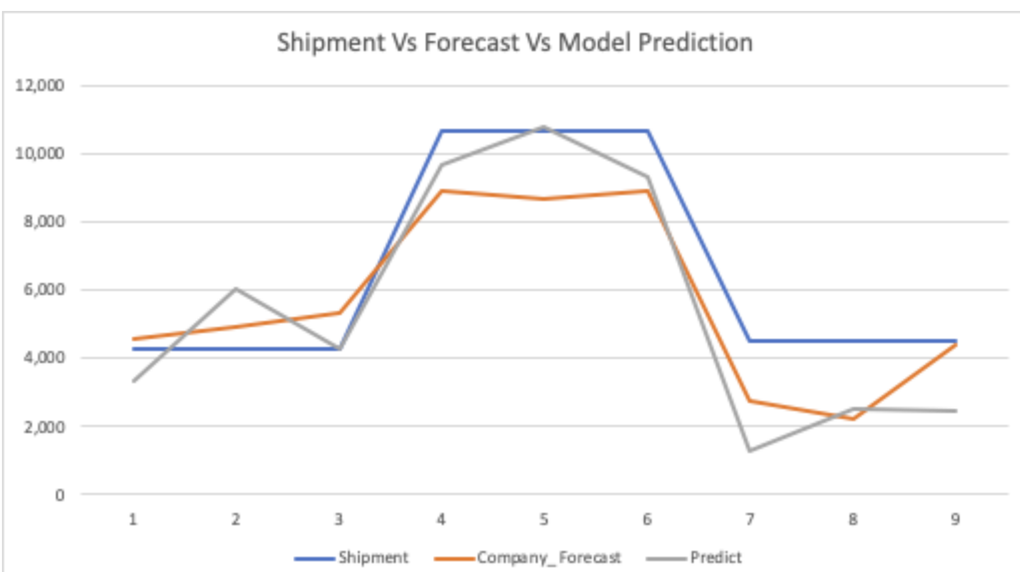


[Figure 14: Residuals Histogram]

After that we predicted the forecast on the testing data, and we noticed some bias in the values. In Table 2, we present the difference between actual forecast and model forecast, and we can see an improvement in Brand2, where the current forecasting method has outperformed in other two brands. In Figure 15, we show the difference between the predicted values, shipments, and actual forecast on a nine-month timeline.

[Table 2: accuracy measure comparison between original forecasting method and regression model]

	RMSE		MD		A-MAPE	
	Original Forecast	Model Forecast	Original Forecast	Model Forecast	Original Forecast	Model Forecast
Brand1	3512.67	3758.9	594.3	-21.4	68%	77%
Brand2	7522.65	10659.3	1083.1	3769.9	66%	66%
Brand3	2675.74	2439.5	1015.5	1418.3	76%	65%



[Figure 15: Shipment vs Internal Forecast vs Model Prediction]

B. October 2017 - September 2018 (Sellout & Inventory)

Intuitively, we initially assumed that the sellout and inventory data from the downstream would mostly affect the shipment of the company. Therefore, we started the analysis by assuming that sellout and inventory level would explain the shipment of the company. Below is the result for the regression analysis (See Figure 16).

i) Brand 1

R Square	0.42			
Adjusted R Square	0.29			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	16469.19	6246.70	2.64	0.03
Sellout	-0.56	0.59	-0.95	0.37
Inventory	-0.15	0.06	-2.56	0.03

ii) Brand 2

R Square	0.54			
Adjusted R Square	0.30			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	26658.84	10597.08	2.52	0.03
Sellout	-0.87	1.00	-0.87	0.41
Inventory	-0.19	0.10	-1.93	0.09

iii) Brand 3

R Square	0.56			
Adjusted R Square	0.31			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	5333.31	1359.58	3.92	0.00
Sellout	-0.17	0.55	-0.31	0.76
Inventory	-0.18	0.10	-1.75	0.11

[Figure 16. Regression analysis on Sellout & Inventory data]

Unfortunately, the independent variables for this model (sellout and inventory) do not explain the shipment of the company, because the adjusted R squares of each model are very low (0.30, 0.14, 0.16). When analyzing the *p*-values of independent variables, inventory level seems to explain more about the shipment rather than sellout data. For Brand 1, *p*-value for inventory (0.03) is significantly lower than that of sellout (0.36), indicating that inventory level explains the volume of shipment significantly. Also, Brand 2 and Brand 3 have the similar outcome, where p-values for sellout are 0.40 and 0.76 and p-values for inventory are 0.08 and 0.11. As a next step, we decided to add more variables to analyze the effect of those variables.

C. October 2017 - September 2018 (Sellout, Inventory, Sales Target & CFR)

We added more variables to the previous model. We analyzed how the sales target and CFR contribute to the explanation of the shipment of the company (See Figure 17).

i) <u>Brand 1</u>

R Square	0.25			
Adjusted R Square	-0.18			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	6137.92	10992.17	0.56	0.59
Sellout	0.10	0.36	0.28	0.78
Inventory	-0.31	0.30	-1.00	0.35
BB	-0.02	0.12	-0.19	0.86
CFR	2495.25	16132.42	0.15	0.88

ii) <u>Brand 2</u>

R Square	0.65			
Adjusted R Square	0.45			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	-5851.33	20061.34	-0.29	0.78
Sellout	0.01	0.86	0.01	0.99
Inventory	-0.11	0.09	-1.25	0.25
BB	-0.17	0.11	-1.58	0.16
CFR	26729.86	16441.79	1.63	0.15

iii) Brand 3

R Square	0.75			
Adjusted R Square	0.61			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	2916.44	1225.10	2.38	0.05
Sellout	-0.75	0.49	-1.53	0.17
Inventory	-0.13	0.08	-1.48	0.18
BB	-0.13	0.25	-0.54	0.61
CFR	3808.02	1251.55	3.04	0.02

[Figure 17. Regression analysis on Sellout, Inventory, Sales Target, and CFR]

Compared to previous models, the R squares of each model have changed. For Brand 1, adjusted R square became negative, which indicates that the model cannot explain the shipment data. However, for Brand 2, adjusted R square has increased from 0.14 to 0.44, improving the previous model. Also, adjusted R square for Brand 3 has increased significantly from 0.16 to 0.61. When analyzing the p-values of each individual independent, many of the p-values stand above 0.10, meaning it is not statistically significant.

Next, we tried to integrate lag between data.

D. October 2017 - September 2018 (Sellout, Inventory, BB & CFR with LAG)

There might exist a certain lag between dependent variable (shipment) and independent variables. we analyzed the correlation between the shipment and various data with different lag in order to identify which lag would mostly explain the model well (See Table 3).

[Table 3. Correlation between independent variable and shipment with different lags. Highlighted are the most correlated data]

i) Brand 1

	Sellout	Inventory	CFR	BB
Ship+0	0.17	**-0.46**	-0.24	-0.03
Ship+1	0.37	0.03	0.21	0.17
Ship+2	**0.43**	0.07	**0.35**	**0.51**
Ship+3	-0.52	0.01	0.05	0.12

ii) Brand 2

	Sellout	Inventory	CFR	BB
Ship+0	-0.07	-0.49	**0.65**	**-0.58**
Ship+1	0.04	-0.61	0.45	-0.41
Ship+2	**0.50**	**-0.68**	-0.16	-0.37
Ship+3	0.20	-0.28	0.26	-0.47

iii) Brand 3

	Sellout	Inventory	CFR	BB
Ship+0	-0.28	**-0.55**	**0.60**	0.18
Ship+1	0.01	-0.05	-0.47	-0.20
Ship+2	**0.41**	0.04	0.17	-0.27
Ship+3	0.17	-0.12	0.45	**0.63**

Brand 1's shipment is mostly correlated by sellout of 2 month before, current inventory level, CFR of 2 month before, and sales target of 2 month before. Likewise, Brand 2's shipment is correlated with sellout of 2 month before, inventory of 2 month before, current CFR, and sales target. Lastly, Brand 3's shipment is correlated with sellout of 2 month before, inventory, CFR, and sales target of 3 month before. we will integrate the lag into the regression model (See Figure 18).

i) Brand 1

R Square	0.33			
Adjusted R Square	-0.05			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	2406.41	10970.98	0.22	0.83
Sellout	0.26	0.30	0.89	0.40
Inventory	-0.17	0.20	-0.86	0.42
BB	0.10	0.14	0.73	0.49
CFR	2506.72	10159.33	0.25	0.81

ii) Brand 2

R Square	0.66			
Adjusted R Square	0.39			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	-9005.29	19370.61	-0.46	0.66
Sellout	0.38	1.05	0.36	0.73
Inventory	-0.11	0.11	-1.03	0.35
BB	-0.06	0.14	-0.45	0.67
CFR	24824.78	21484.96	1.16	0.30

iii) Brand 3

R Square	0.79			
Adjusted R Square	0.68			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	1170.20	1255.48	0.93	0.38
Sellout	0.39	0.35	1.09	0.31
Inventory	-0.19	0.06	-3.15	0.02
BB	0.48	0.26	1.86	0.10
CFR	1762.87	1009.87	1.75	0.12

[Figure 18. Regression analysis on Sellout, Inventory, Sales Target, and CFR with Lag]

Revised model for Brand 1 did not improve at all. Its adjusted R square is still negative value. Also, the adjusted R square of revised model for Brand 2 decreased from 0.45 to 0.39. On the other hand, adjusted R square for Brand 3 improved and increased from 0.61 to 0.68. Many of the independent variables are not statistically significant due to high p-value, but the inventory level seems to have relatively low p-value for all brands.

E. Result for brand level regression analysis

We compiled the RMSE, A-MAPE, and MD to compare the forecasting accuracy of each model (See Figure 19). However, for brand level, we concluded that original model has the best forecasting accuracy.

In terms of RMSE, model A has good forecasting accuracy in Brand 3 and, model C and D have improved accuracy in Brand 2. In terms of A-MAPE, model A has improved accuracy among two categories (Category 2 and 3).

RMSE					
	Original	Model A	Model B	Model C	Model D
Brand 1	3.5	3.7	7.2	3.6	3.7
Brand 2	7.5	10.6	7.9	7.1	6.2
Brand 3	2.6	2.4	3.9	4.0	2.7
A-MAPE					
	Original	Model A	Model B	Model C	Model D
Brand 1	68%	77%	147%	53%	81%
Brand 2	66%	66%	71%	68%	61%
Brand 3	76%	65%	99%	100%	68%

MD					
	Original	Model A	Model B	Model C	Model D
Brand 1	0.5	-0.02	6.6	-1.7	1.2
Brand 2	1.1	3.8	4.7	6.0	6.6
Brand 3	1.0	1.4	-3.8	-3.9	-0.6

[Figure 19. Metric comparison in Brand level regression analysis.

Highlighted are the figures that were improved]

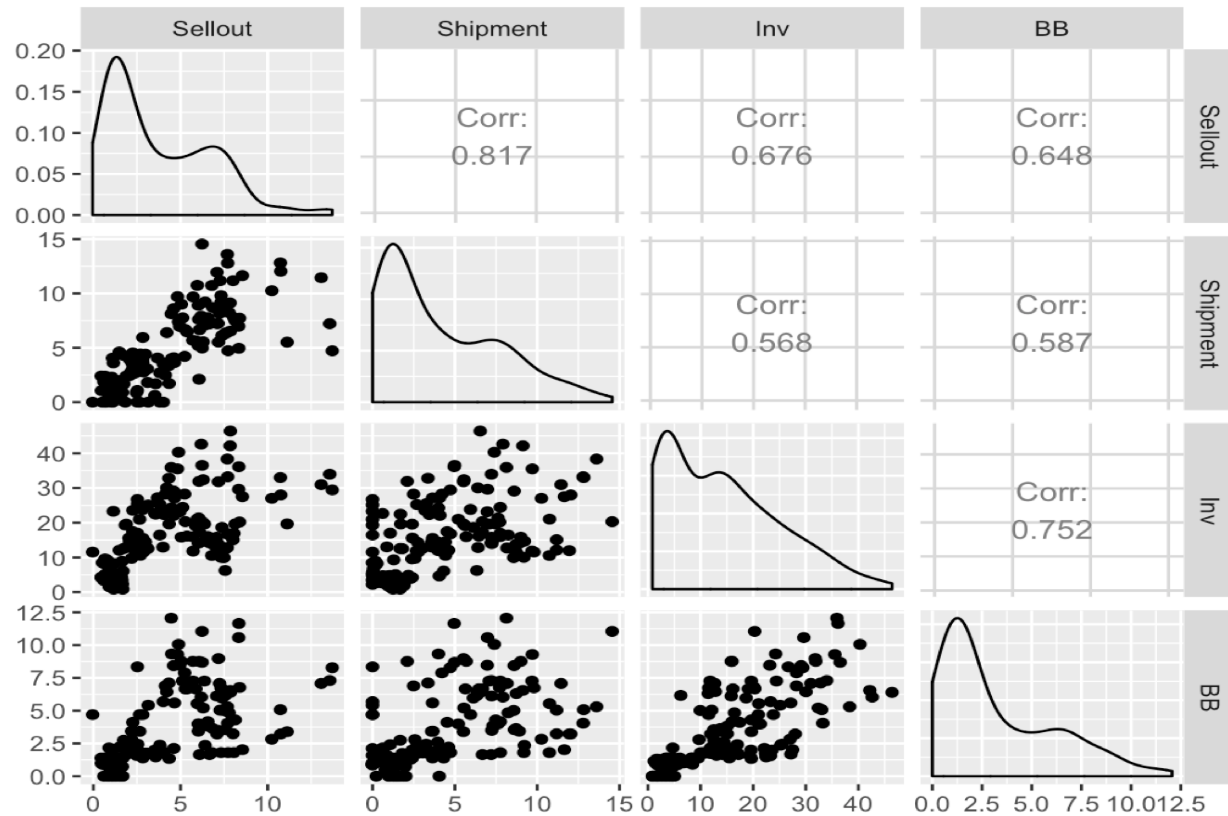
As a next step, we will conduct regression analysis on category level.

4.1.3. Regression Analysis (Category level)

The company groups the SKUs by either brand or category. In order to compare the regression model between brand and category, we also conducted regression analysis on category level.

We extracted the data on the category-level with the same criteria of brand-level analysis (i.e. sellout, inventory level, building block, customer fill-rate (CFR), orders, shipment, and forecast data).

A. With the same underlying parameters used in Section 6.1.1 A, we plot shipment data and other three predictors (see Figure 20). Below the diagonal are the scatter plots where variable name indicates y-axis variable. For example, the plots in the bottom row have building blocks (BB) on the y-axis (which allows studying the individual outcome-predictor relations). We can see different types of relationships from different shapes, where most of the relations are linear apart from the relation between BB and shipment. We observed that BB and inventory has high correlation which will cause multicollinearity in the regression model. We will use Inventory as a predictor for shipments, and BB as a the only predictor for Sellout. Sellout then is going to be used as a predictor for shipment which will give the flexibility to predict shipments with respect to the availability of building block.

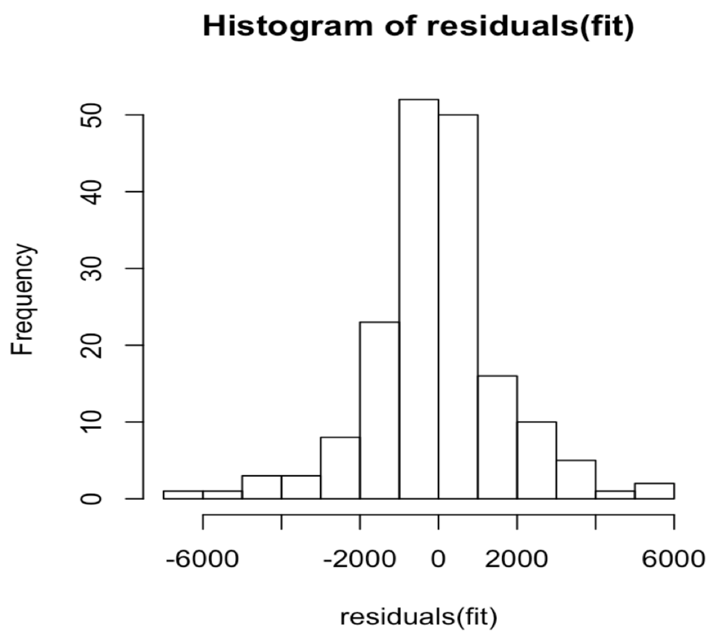


[Figure 20. Scatter plot matrix for shipment and other three numeric predictors in 1,000 unit]

We run the regression model with the above predictors on 5 categories and also investigated seasonality effect on the shipment volume. Moreover, we found that Inventory and sellout of the period prior to shipment are more correlated with shipment volume than the current period figures. Building blocks and seasonality were also not significant with high p-value greater than 0.05. The final model was able to capture 76% of the variation. We also validated the distribution of the difference between prediction and actual shipment volume and we found that it is normally distributed as shown in Figure 21. The regression equation for Sellout and shipment is as follows:

$$Sellout = 8291.22 - 45.18 * log(BB + 1) - 6818.99 * (Category\,2) - 1788.95 * (Category\,3) - 7033.47 * (Category\,4) - 5170.5 * (Category\,5)$$

$$Shipment\ volume = 8.399e + 03 + 2.552e - 01 * (Sellout\ t - 1) - 6.535e - 02 * (Inventory\ t - 1) - 7.957e + 02\,(Events) - 7.228e + 03 * (Category\,2) - 1.691e + 03 * (Category\,3) - 6.978e + 03 * (Category\,4) - 5.023e + 03 * (Category\,5)$$



[Figure 21. Difference between actual and predicted values]

We forecasted the shipment based on testing dataset (See Table 4). In terms of RMSE, three categories (Category 1, 4, and 5) slightly improved by 13%, 15%, and 7%. In terms of A-MAPE, four categories (Category 1, 3, 4, and 5) improved by 6%, 5%, 18%, and 9%.

[Table 4: Accuracy measure comparison between original forecasting method and regression model]

	RMSE		MD		A-MAP	
	Original Forecast	Model Forecast	Original Forecast	Model Forecast	Original Forecast	Model Forecast
Category 1	6.1	5.3	-2.5	-0.3	63%	59%
Category 2	0.7	0.9	0.1	0.1	77%	88%
Category 3	3.9	4.1	1.5	1.7	92%	87%
Category 4	1.9	1.6	-0.8	-0.6	87%	71%
Category 5	2.7	2.5	-1	-1.1	76%	69%

B. October 2017 - September 2018 (Sellout & Inventory)

In general, the models based on category have lower adjusted R square than models based on brand (See Figure 22). It means that category level shipments are harder to explain with sellout and inventory variables. Especially, the models for Category 1, Category 2, and Category 3 are statistically not significant, because they have adjusted R square close to 0.

p-values for Category 1, Category 2, Category 4, and Category 5 intercepts are significant because they are close to 0 value. The value of the intercept is a prediction for the value when all independent variable becomes zero. That is, predicted shipments for those categories tend to become close to the intercept values significantly.

Also, the result of Brand 3 and Category 5 are exactly the same. This is because Brand 3 only manufactures Category 5.

i) Category 1

R Square	0.22			
Adjusted R Square	0.05			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	12100.72	3091.95	3.91	0.00
Sellout	-0.04	0.22	-0.18	0.86
Inventory	-0.17	0.11	-1.60	0.14

ii) Category 2

R Square	0.00			
Adjusted R Square	-0.22			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	1198.72	525.00	2.28	0.05
Sellout	0.13	0.64	0.20	0.85
Inventory	-0.01	0.15	-0.04	0.97

iii) Category 3

R Square	0.21			
Adjusted R Square	0.03			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	8874.83	12554.96	0.71	0.50
Sellout	0.23	1.96	0.12	0.91
Inventory	-0.20	0.21	-0.97	0.36

iv) Category 4

R Square	0.53			
Adjusted R Square	0.43			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	4728.59	1286.43	3.68	0.01
Sellout	-1.39	0.75	-1.86	0.10
Inventory	-0.21	0.13	-1.65	0.13

v) Category 5

R Square	0.31			
Adjusted R Square	0.16			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	5333.31	1359.58	3.92	0.00
Sellout	-0.17	0.55	-0.31	0.76
Inventory	-0.18	0.10	-1.75	0.11

[Figure 22. Category level regression analysis on sellout & inventory data]

C. October 2017 - September 2018 (Sellout, Inventory, Sales Target & CFR)

When we incorporate sales target and CFR data into the previous analysis (Analysis B), we could notice that adjusted R squares for all the model, except Category 1, increases (See Figure 23). Through integrating those data into the model, the model could be better explained to determine the shipments. However, adjusted R squares for Category 1, Category 2, and Category 3 models are close to 0.

i) Category 1

R Square	0.39			
Adjusted R Square	0.04			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	4655.15	16357.17	0.28	0.78
Sellout	-0.36	0.38	-0.96	0.37
Inventory	-0.32	0.21	-1.49	0.18
BB	-0.12	0.09	-1.33	0.23
CFR	16005.12	24337.90	0.66	0.53

ii) Category 2

R Square	0.40			
Adjusted R Square	0.05			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	-36697539898	18692075844	-1.96	0.09
Sellout	1.55	1.49	1.04	0.33
Inventory	0.19	0.19	0.99	0.36
BB	-0.31	0.58	-0.53	0.61
CFR	36697540221	18692075556	1.96	0.09

iii) Category 3

R Square	0.51			
Adjusted R Square	0.23			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	5376.09	13533.54	0.40	0.70
Sellout	-0.52	1.79	-0.29	0.78
Inventory	-0.20	0.18	-1.08	0.32
BB	-0.13	0.13	-0.98	0.36
CFR	9203.20	9009.75	1.02	0.34

iv) Category 4

R Square	0.74			
Adjusted R Square	0.59			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	74845.84	30533.17	2.45	0.04
Sellout	-0.44	0.75	-0.59	0.57
Inventory	-0.26	0.11	-2.27	0.06
BB	-0.31	0.53	-0.58	0.58
CFR	-70469.96	31014.71	-2.27	0.06

v) Category 5

R Square	0.75			
Adjusted R Square	0.61			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	2916.44	1225.10	2.38	0.05
Sellout	-0.75	0.49	-1.53	0.17
Inventory	-0.13	0.08	-1.48	0.18
BB	-0.13	0.25	-0.54	0.61
CFR	3808.02	1251.55	3.04	0.02

[Figure 23. Category level regression analysis on sellout, inventory, sales target, and CFR]

D. October 2017 - September 2018 (Sellout, Inventory, BB and CFR with LAG)

To identify the lag among variables, we conducted correlation analysis (See Table 5). Each category has different correlation. For example, Category 1's shipment is mostly correlated to the sellout data 2 month before, while Category 2's shipment is correlated to the sellout data 1 month before.

[Table 5. Category correlation analysis between independent variable and shipment with different lags. Highlighted are the most correlated data]

i) Category 1

	Sellout	Inventory	CFR	BB
Ship 0 Lag	-0.06	**-0.47**	**0.40**	0.19
Ship 1 Lag	0.60	-0.35	0.16	-0.01
Ship 2 Lag	**0.61**	0.17	0.25	**-0.46**
Ship 3 Lag	0.01	-0.47	0.11	0.02

ii) Category 2

	Sellout	Inventory	CFR	BB
Ship 0 Lag	0.07	-0.01	0.45	0.04
Ship 1 Lag	**0.29**	-0.23	**0.55**	0.27
Ship 2 Lag	-0.20	**-0.24**	0.38	**-0.28**
Ship 3 Lag	0.02	-0.10	-0.52	0.00

iii) Category 3

	Sellout	Inventory	CFR	BB
Ship 0 Lag	0.35	-0.45	**0.53**	-0.58
Ship 1 Lag	**0.57**	**-0.57**	0.30	-0.44
Ship 2 Lag	**0.57**	-0.54	-0.41	**-0.60**
Ship 3 Lag	0.33	-0.48	0.29	0.07

iv) Category 4

	Sellout	Inventory	CFR	BB
Ship 0 Lag	**-0.62**	-0.59	-0.67	-0.01
Ship 1 Lag	-0.39	-0.37	**-0.87**	0.26
Ship 2 Lag	-0.34	**-0.79**	0.32	**0.33**
Ship 3 Lag	-0.46	0.01	-0.82	-0.01

v) Category

	Sellout	Inventory	CFR	BB
Ship 0 Lag	0.28	-0.55	0.60	0.18
Ship 1 Lag	**0.01**	-0.05	**-0.47**	-0.20
Ship 2 Lag	0.41	**0.04**	0.17	**-0.27**
Ship 3 Lag	0.17	-0.12	0.45	0.63

we integrated this lag information into the regression model (See Figure 24). The adjusted R squares of four models improved comparing to the previous model (Analysis C). Especially, Category 2's adjusted R square improved the most, changing from 0.05 to 0.31.

i) Category 1

R Square	0.51			
Adjusted R Square	0.23			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	-12176.38	18896.45	-0.64	0.54
Sellout	0.63	0.34	1.84	0.11
Inventory	-0.18	0.14	-1.34	0.22
BB	0.14	0.09	1.50	0.18
CFR	19042.58	19463.05	0.98	0.36

ii) Category 2

R Square	0.62			
Adjusted R Square	0.31			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	17728299122	25407715396	0.70	0.52
Sellout	1.23	1.37	0.90	0.41
Inventory	-0.12	0.14	-0.87	0.42
BB	-0.73	0.61	-1.20	0.28
CFR	-17728297469	25407715268	-0.70	0.52

iii) Category 3

R Square	0.66			
Adjusted R Square	0.43			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	10368.49	15874.45	0.65	0.54
Sellout	-0.80	2.07	-0.39	0.71
Inventory	-0.26	0.19	-1.38	0.22
BB	-0.29	0.18	-1.60	0.16
CFR	7110.66	7469.50	0.95	0.38

iv) Category 4

R Square	0.99			
Adjusted R Square	0.97			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	39460.31	5772.26	6.84	0.00
Sellout	-0.40	0.14	-2.91	0.03
Inventory	-0.14	0.02	-7.82	0.00
BB	0.08	0.24	0.33	0.75
CFR	-37288.99	6011.60	-6.20	0.00

v) Category 5

R Square	0.79			
Adjusted R Square	0.68			
Variables	*Coefficients*	*Standard Error*	*t-Statistic*	*P-Value*
Intercept	1170.20	1255.48	0.93	0.38
Sellout	0.39	0.35	1.09	0.31
Inventory	-0.19	0.06	-3.15	0.02
BB	0.48	0.26	1.86	0.10
CFR	1762.87	1009.87	1.75	0.12

[Figure 24. Category level regression analysis on sellout, inventory, sales target, and CFR with Lag]

E. Result for category level regression analysis

For category level regression, we compiled the RMSE, A-MAPE, and MD to compare the forecasting accuracy of each model (See Figure 25). In terms of RMSE, model A has good forecasting accuracy in Category 1, Category 4, and Category 5 and model B has best accuracy for Category 3. For Category 2, original model has the best output. In terms of A-MAPE, model A has the improved accuracy among four categories (Category 1, 3, 4, and 5)

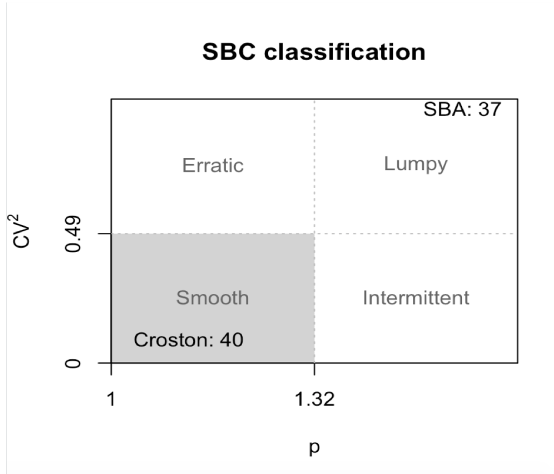
RMSE					
	Original	Model A	Model B	Model C	Model D
Cat 1	6.1	5.3	5.5	6.5	6.5
Cat 2	0.7	0.9	0.8	1.4	0.9
Cat 3	3.9	4.1	3.6	4.0	5.0
Cat 4	1.9	1.6	2.2	1.6	1.4
Cat 5	2.7	2.5	3.9	4.0	2.8

A-MAPE					
	Original	Model A	Model B	Model C	Model D
Cat 1	63%	59%	57%	69%	81%
Cat 2	77%	88%	84%	149%	90%
Cat 3	92%	87%	75%	81%	111%
Cat 4	87%	71%	138%	89%	79%
Cat 5	76%	69%	99%	100%	67%
MD					
	Original	Model A	Model B	Model C	Model D
Cat 1	-2.5	-0.3	-1.5	-5.1	1.0
Cat 2	0.1	0.1	0.4	1.3	0.3
Cat 3	1.5	1.7	0.2	0.0	-2.9
Cat 4	-0.8	-0.6	0.6	0.8	-0.1
Cat 5	-1	-1.1	-1.5	-1.6	1.6

[Figure 25. Metric comparison in Category level regression analysis in 1,000 units. Highlighted are the figures that were improved]

4.1.4. Croston Method

we applied Croston's method to identify a better way for forecasting. We started by classifying the items as proposed by (Williams TM, 1984) and illustrated in Section 2.3. To do so we first have to remove items that didn't have more than two observations across the underlying time horizon (12 months). Then we classified the items (see Figure 26), where 37 SKU were more suitable for forecasting with SBA method, and 40 SKU were identified as suitable for forecasting with the Croston approach.



[Figure 26. Item classification for Croston and its variation]

A. SKU level analysis

[Table 6. Improvement of forecasting accuracy in SKU]

Improvement	# of SFU	% of SFU
20%~	14	19%
10~20%	12	16%
0~10%	20	27%
No Improv	28	38%
Total	74	100%

When we conducted Croston's method in each SKUs (See Table 6), we identified that approximately 62% of the SKU improved in terms of RMSE metric. Specifically, 27% of the SKUs improved by 0~10% and 19% of the SKU improved more than 20%. On the other hand, 38% of SKUs did not improve in terms of forecasting accuracy.

B. Brand level analysis

[Table 7. Improvement of forecasting accuracy in brand]

	RMSE_Croston	RMSE_Internal	Improve
Brand1	1,527	1,608	5%
Brand2	4,206	2,372	-77%
Brand3	1,236	1,213	-2%

we aggregated the SKU into brand level, and we compared the metrics. Even though forecasting accuracy of many SKUs improved, there is very little or no improvement from a brand perspective. Brand 1 was the brand with only improvement with rate of 5%. This might be caused by the fact that few SKUs in Brand 2 and Brand 3 with low forecasting accuracy dominates the overall forecasting accuracy.

C. Category level analysis

The result of category level analysis (see Table 8) is similar to that of brand level analysis. While Category 2 and Category 5 improved in terms of RMSE, forecasting accuracy of Category 2, Category 4, and Category 5 did not improve.

[Table 8. Improvement of forecasting accuracy in Category in 1,000 Units. Highlighted are the figures that were improved]

	RMSE			MD			A-MAPE		
	Original Forecast	Model Forecast	Croston	Original Forecast	Model Forecast	Croston	Original Forecast	Model Forecast	Croston
Cat 1	6.1	5.3	5.4	-2.5	-0.3	-1.3	63%	59%	54%
Cat 2	0.7	0.9	0.8	0.1	0.1	0.3	77%	88%	78%
Cat 3	3.9	4.1	4	1.5	1.7	1.9	92%	87%	89%
Cat 4	1.9	1.6	2.1	-0.8	-0.6	-1.5	87%	71%	95%
Cat 5	2.7	2.5	2.9	-1	-1.1	-1.5	76%	69%	81%

4.1.5. Regression Analysis (SKU level)

We conducted multi-regression analysis at the category level and compared the results with the internal forecast model. In order to forecast at the SKU level, we predicted the shipments at the category level and broke them down to the SKU level. Shipment volumes for each category were split based on each SKU's contribution to the total category volume. This was done by calculating the average of the previous year's shipments (i.e., Oct. 2017 - Sept. 2018). Below are the detailed approach and the results for analysis.

A. *Forecasting the future demand (sellout) and integrating the demand into the model.* We could predict the demand by using sales target data (building block). Then, we used the predicted sellout data as an explanatory variable to predict shipments, which provided a shipment forecast for three months. This can be forecasted over a longer time period subject to the availability of building block data. As for the results, 78 SKUs were improved in terms of RMSE (see Table 9), while 37 SKUs were not improved. We were unable to calculate improvement for another 101 SKUs, since there were no internal forecast for those SKUs.

[Table 9. Improvement of Forecasting Accuracy in SKU. Regression Analysis based on Forecasting Demand. Unit is number of SKU. Accuracy is calculated in RMSE]

	Oct	Nov	Average
20%~	71	63	61
10~20%	3	5	12
0~10%	4	10	16
No Improv	37	37	36
N/A	101	101	91
Total	**216**	**216**	**216**

B. *Training the model with lag t-3.* Based on the correlation analysis between independent (ex. sell-out, inventory) and dependent variables, the best correlation was with lag t-0 (Section 3.4.2). However, the lag of t-3 also has a similar correlation, so we trained the model with t-3 lag in order to predict the long-term shipment (i.e., after 2 months). The results were that 77 SKUs improved in terms of RMSE (see Table 10), while 38 SKUs did not improve. Similar to Analysis A, we could not calculate improvement for 101 SKUs.

[Table 10. Improvement of Forecasting Accuracy in SKU. Regression Analysis based on Lag t-3 Training. Unit is number of SKU. Accuracy is calculated in RMSE]

	Oct	Nov	Average
20%~	70	64	63
10~20%	2	6	6
0~10%	5	7	20
No Improv	38	38	36
N/A	101	101	91
Total	**216**	**216**	**216**

5. DISCUSSION

5.1. Limitations

There are some limitations to the analysis. Below are the limitations that can be addressed through further research.

- The company has not gathered the data for a long time. Since the data of inventory level was accessed after October 2017, we were only able to conduct the regression model with 12 observations. Furthermore, when we analyzed the lag between the independent variables and dependent variable, the observation that we could use decreased to 10. The result would have been much more statistically significant, if we had data for more than 12 observations.

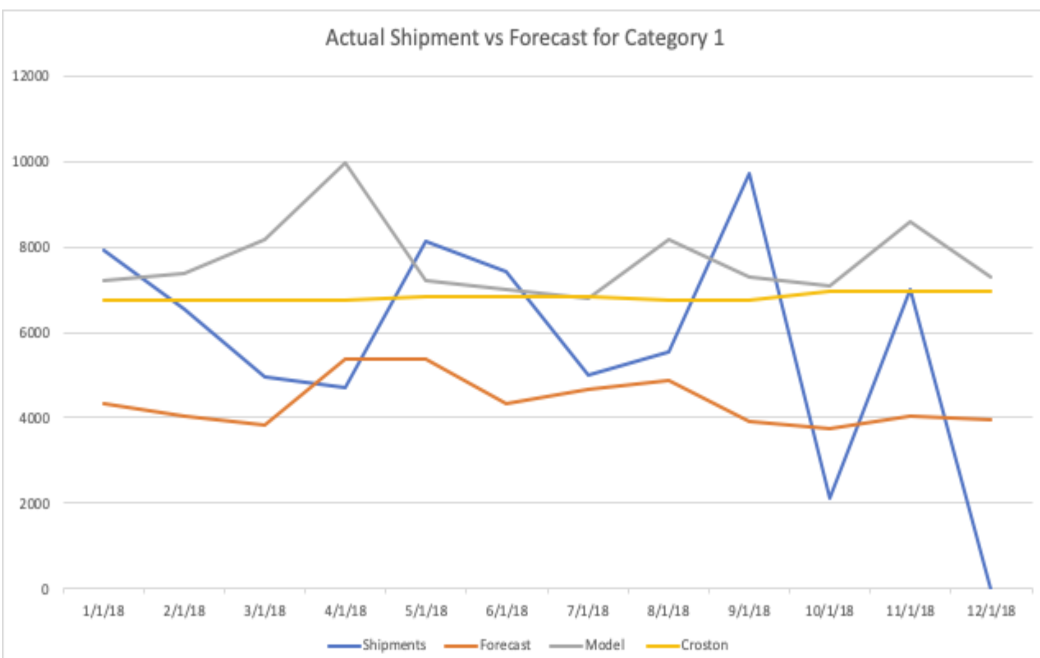
- Initially we identified ten data points that might be useful for forecasting. However, we were able to access data for 5 data points. We expect that if we could gather data such as POS data and competition prices, then forecasting would be much accurate.
- There were also unusual circumstances that we and the company could not explain. For example, sales target data has increased exponentially after July 2018. Also, forecasting numbers were not developed in December 2017. If we had been able to identify the underlying cause of those circumstances, we could have replaced the numbers with an imputed value.
- There are lots of fluctuation in company's SKU. This is because while company maintains best-selling products, it also develops new products and scrap the old products. These fluctuation and changes in SKU impact the forecasting model. Since the model is trained on different set with different SKUs, it might negatively affect the testing model.

6. Conclusion

6.1. Insights and Management Recommendations

After we conducted the analysis, we noticed that some forecasting methods outperform other techniques in some categories. Each method has its own benefits and limitations. For example, as shown in Figure 27, Croston's method maintains a stable level across the time horizon which will positively impact the upstream manufacturing in terms of planning and setting inventory levels, as it doesn't get affected by the lumpiness of the demand. The current forecasting method of moving average also has a benefit of higher accuracy in some of the categories, however, moving average gets affected by periods that has no demand and may cause some disruption in upstream if the there are multiple periods with zero demand. The multi-tier regression analysis has a benefit of integrating the downstream distributor data, and it has improved the accuracy in 4 out of 5 categories in terms of A-MAPE as shown in section 6.1.4 Table 9. However, it's high dependent on the accuracy and the availability of these data.

To achieve a better forecast accuracy, we suggest capturing all activities that the demand team perform on the statistical forecast to transform it to the final version shared with finance. For example, if the forecast in July is X, and demand forecast team adjusted this volume by a certain percentage due to promotion, economy downturn or any other reason. Recording these adjustments will be useful for a future research. Moreover, for better accuracy, distributors are encouraged to log their inventory balance each month for better accuracy instead of calculating it backward from the current period. As some of the inventory buckets on the system may be missed due to system limitations, such as in-transit inventory.



[Figure 27. Shipment vs forecast techniques comparison for category 1 on 2018]

6.2. Future Research

With the objective of improving the accuracy of forecasting model, we propose some points for future research.

- In the future, we propose to conduct the regression analysis with more data. Currently the company has collected data after October 2017, leading to limited number of data. We had only 12 observations for inventory data, limiting the model's statistical significance. However, if we conduct the regression model one year later, we would have double the data and better understanding statistical model.
- We propose to integrate data with more data points. Due to limited access to downstream data, we could conduct with only four independent variables. However, if the company would be able to link more data from downstream (i.e. distributor and retailer), we could have various data points to integrate in the model and have better forecasting accuracy.
- Also, we propose to conduct with various categorization theme. In this research, we categorized the SKUs with the brand and category, which were already given by the company. We further categorized the SKU by the lumpiness and smoothness based on SBA method mentioned in section 2.3. However, if we could find better way to categorize the SKUs with similar behavior, that could lead to improved forecasting method.

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