Owens Illinois Case Competition

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Contents

1 Executive Summary

This report provides an analysis of Owens-Illinois shipment data, which helps Owens Illinois better forecast the shipment and to assist them better segment their products and customers. The report first deals with exploratory data analyses, such as the counts of product types, yearly orders, and returns, the distinction of unique customers and customer characters as well as the times series plot of shipment tons in order to better understand the dataset. The report then focuses on model building, which can be divided into two parts. The first part is to build the models shipment Tones by country-categories, to compare the models for each category under the countries, to choose the best model to generate forecasts from May 2017 to August 2017. The second part of the report talks about the results from the forecasts in details and also the results from segmentation of products. The report then provides suggestion on how to segment the customers that should help Owens Illinois maintain a good relationship with the "important" customers. The original dataset that O-I provided includes the Shipment Tons in 6 countries (Congo, Finland, India, Uganda, South and North East of Belize). We selected the Shipment (in tons) as the time series variable. Also, the O-I dataset contains variables, such as Material, Product Category, Customer Name ID, Forecast Tones. Throughout the analysis, we used different methods to generate the results. Finally, we hope to achieve two goals. First, to derive a model to forecast the Shipment Tons for every category in every country. This will lead to a more accurate and detailed forecast. Second, it will segment the products using demand and growth, which will allow O-I to "visualize" different clusters of products in time, so that they can customize their policies to the needs of specific the customers' needs. This should allow O-I to make better efforts to communicate with their customers in order to achieve an opportunity for growth in sales and to make better profits. We transformed some of variable names from the original O-I data set. Miscellaneous was 'misc' and Not Assigned was 'unknown'.

2 Data Analysis

In this segment, we present the details of the data set structure and the initial set of findings. The exploratory data analysis presented in this segment covers all products across all destination countries. The EDA gives us first glance into the data, explores hidden trends, computes summaries, and draws comparisons between product categories.

2.1 The Data

The theme of the data set is based on the total tones of glass bottles shipped for a specific type in a specific country on a specific date and time. Specifically, there were two nominal variables – *Sales Org*, *Product Category*, and *Customer Name*. The date-time variable was called Month and the two continuous variable were *Shipment Tonnes* and *Forecast Tonnes*.

The categories of products represent the product line of Owens Illinois. The product categories are mostly consistent across all countries with a few exceptions. The most consistent categories were beer, non-alcoholic beverages, wine, spirits and RTD-FAB. The other feature in the data set was the total volume (in tons) of a product that was shipped on a specific date. Though the details of shipment origin are missing, the data does give us an indication of shipment destination. The volume figures are integers with a few negative values indicating possible return of shipment. The date of shipment is always on the first of every month for a year. This makes it impossible to reveal the daily trends in volume. Consequently, we had to assume that shipment goes out once a month to a specific destination and aggregate the volume figures by month to model or to analyze data. In other words, we are dealing with monthly values of time series. The other less significant features of the data set were the type of material shipped and the customer name. Due to reasons of confidentiality the names of the customers were masked which also meant that the analysis lost crucial information especially in terms of geographically isolating the customer segments within a country for more detailed insights. Nevertheless, we were able to extract the number of unique customers for a country within a specific product category within a specific time frame. As we will see later on, this becomes a very important contributor to the segmentation strategy we formulate.

2.2 Exploratory Data Analysis

India: [2] shows that wine dominates the number of shipment tons for India. The other prominent categories are non alcoholic beverages, beer, spirits and RTD-FAB. This sheds some light into the overall market size of wine bottles relative to the other categories. When we breakdown [2] into years in [3], more hidden trends emerge. The overall orders for wine are not only high, their numbers have been climbing steadily over the years. [3] also reveals that the other product categories have more or less stagnant growth rate. The time series of the shipment tons of the individual categories in [4] show that beer, food and spirit bottle shipments have steadily declined over the years. Only wine and non-alcoholic beverages have shown signs of improvement while RTD-FAB have been stagnant over the years. [5] which displays the mean annual shipments agree with the above conclusions. Another indication of demand would the number of unique customers every year which is shown in [6]. Wine has shown a steady increase in customers whilst the other bottle category has been more or less stagnant over the years. Interestingly, [Table 1] shows that the top 20 customers (by sales volume) has a fair share of RTD-FAB (wine dominates as usual) when we were expecting food bottles to be the among the top buyers. Further investigations on the relative proportion of product segments within every quartile of the sales volume as shown in [Table 2] reveals some interesting patterns. Wine has dominating presence across all segments implying that there are buyers with varying demand. This also shows why food didn't appear a lot in our top 20 customers. Second in line after wine is food. There are more food bottle buyers in the higher quartiles which could indicate that customers prefer bigger shipments. Beer and spirits are consistent across all quartiles.

Uganda: [7] shows that beer and unknown category dominates the order count.The other prominent groups are spirit, wine, drugs and chemical and non alcoholic beverages. When we break down this picture by years in [8] it shows that beer bottle shipment tons are higher than most others but it has been steadily decreasing. Unknown category gets a big leap in terms of orders from 2013 to 2014 but then decreases. The story is the same for other categories except spirit bottle whose numbers have increased. [9] shows the time series of the shipment tons for each category. The trends are similar to the number of orders. All categories except non alcoholic beverages and spirits have the declining trends. Beer shows a clear periodic seasons. The seasonality is not that obvious in food, spirit and wine.The mean annual tons shipped over the years in [10] shows a downward trend for beer and food but spirits and non alcoholic beverage segment show an upward movement. [11] reveals the unique customer count over the years. This too like the [9] show the numbers have been falling for most categories even for spirits which did account for a slight increase in orders over the years. When individual customers were sorted in [Table 3] by total volume of tons, beer dominated the list. This means the more consistent and 'bigger' customers in Uganda are buyers of beer. When we looked at each quartile of sales volume in [Table 4], an interesting pattern emerged. Turns out beer, drug-chemical and unknown categories dominate the lower 25% of volumes shipped. So customers within these categories have lower quantity demands. This changes in the next quartiles as the difference between beer and drugs and chemical increase. Beer has the larger share in the top 25% of sales volume. There are more wine buyers in the top 50% of sales volume. So, wine customer have higher demand in terms of sales volume. This could reflect the market needs for wine in Uganda.

Finland: [12] shows that wine is the dominant product category for Finland. The other significant product categories are miscellaneous, food and spirits. This dominance is also reflected in the annual count of orders in [13]. This also shows that wine export numbers has been increasing. For miscellaneous or food the numbers keep falling across the years. [14] shows the time series of volumes all the product categories. For wine we can see a clear seasonal movement across the years. The same cannot be said for food or spirits. Their movements seem random. Surprisingly NAB and beer show significant volume of shipment even though the number of orders were low. Perhaps they were shipped in larger quantities. In [15] it becomes clear that indeed beer and NAB had higher volumes of shipments. [16] shows the total number of unique customers for each product category over the years. Wine is leaps ahead of all categories. Although the number slightly fell in 2014, it quickly picked up. When individual customers were sorted by total shipment tons in [Table 5], wine stood out as the dominant category. Surprisingly beer and NAB were in the top 3 spots. This helps reconcile our previous beliefs that beer and NAB are shipped in larger quantities. To gain deeper insights into customer behavior, we split the sales volume into quartiles in [Table 6] and inspected the proportion of product category within each quartile. Wine dominates the proportion of products in every quantile. This implies there are buyers with varied demands of wine in Finland. Spirits, miscellaneous and NAB take up significant shares in the lower 25% volumes shipped. Spirit numbers fall within the subsequent quartiles but they spike up again in the upper 25%. This implies customers buying spirit usually have larger or very small shipment demands. The other categories stay steady across the quartiles except food which drastically increases in proportion in the final quartile revealing why we saw a large number of orders for food in [12].

Congo: [17] shows that unknown, food, NAB, drugs and chemical, spirits and beer are all significant categories. The annual order count in [18] breaks up [17] by year. Here we can visualize the trends in order count. Unknown category has been increasing steadily over the years. This is the same for all product categories that are significant in their order count. When we look at the time series plots for volumes for all categories in [19], we see that wine, RTDFAB, beverage and miscellaneous does not have significant volumes of products being shipped over the years. Beer and spirits have visible seasonal patterns while unknown seems to have an upward trend. [20] also displays the volume shipped for each category in the form of bar plots. It is interesting to note that although unknown had the larger share of orders, RTDFAB had the largest shipment volume. Beer which had significantly smaller share of orders follows RTDFAB in terms of shipment volume. The trend of shipment tons across the years however is decreasing for unknown, RTDFAB and beer. Only food has a slightly increasing trend in terms of volume. [21] shows the unique customer count for each category. Like [17] unknown category has the largest fraction of buyers, although their numbers fall at the end. This pattern is repeated for food and drug and chemicals. Only RTDFAB and spirits have an upward trend. When individual customers were sorted by sales volume in [Table 7] the dominating category were beer and nab. When we broke down sales volume by quartiles in [Table 8] we found there were higher proportion of beer in the fourth quartile. This means that customers buying beer usually have higher demands in terms of volume. The reverse is true for unknown category. Spirts, food, NAB and drug and chemical on the other hand have buyers across every quartile.

North-East Belize: [22] shows that North-East Belize has a wide variety product categories with significant order counts. When this is broken down annually in [23] interesting trends emerge. The trend that stands out is from drugs and chemicals- their number fall drastically within a few years. The other worrying sign is for food, beer and NAB whose numbers also decline over the years. Only beer and spirits show a positive upward trend. When we focus on shipment tons time series in [24] we discover that although beer had a positive trend in terms of number of orders, the volume in tons has a decreasing trend. Spirits and wine has an almost invisible seasonal component to them. RTDFAB and drugs and chemical numbers almost flatline over the years. Food, NAB, unknow and wine all have decreasing trends in terms of sales volume. This decreasing trend becomes more clear with [25]. [26] show unique customer count. This has almost an identical trend as [23] with the huge drop for RTDFAB and steady drops for unknown, food and spirits. When customers were sorted by total volume in [Table 9], the top 20 customers had more beer, spirits and NAB. This shows these categories could have the 'bigger' customers. To confirm we further investigated the quartiles of sales volume in [Table 10] for anomalies. It solidifies the above conclusion and adds unknown category to the list of products that customers prefer to buy in larger quantities. Drugs and chemicals on the other hand have more buyers with smaller demands in terms of volume.

South-East Belize: [27] shows the order count for each product. Unlike NE Belize, the unknown category in south east dominates over other categories. The other significant categories include food, spirit, NAB, wine, beer and RTDFAB. [28] breaks down [27] by years. The trends are more positive for south east than for north east. The order count increases across all categories for over the years. Time series plot of the volume for shipment tons show that beer, RTDFAB, spirits, unknown and wine have a seasonal component to the time series. The time series for food and NAB are quite random [29]. The trends in the time series become more clear with [30]. All category have a decreasing trend in terms of volume. [31] show unique customer count. These show positive signs for all categories with the numbers increasing over the years. When we arranged the customers by sales volume the top 20 customers in [Table 11] had a mix of all product categories. When we split the volume by quartiles in [Table 12], food, beer, NAB and unknown and wine occupy the top quartile. When we go to the lower quartiles, we find that unknown has a higher fraction suggesting customer prefer to buy products within this segment in smaller quantities. The reverse is true for beer, NAB and wine.

3 Modeling and Segmentation Approaches:

The segment is split into three part – the first part we outline the statistical methods used to model the time series. In the second, we discuss the validation approach and in the third we layout the framework we used to segment the product and customers.

3.1 Time Series Modelling:

The appropriate stochastic variable to model was the volume (in tons) of a product. In the time series each row for a specific product was the monthly aggregate of volume. Please note that the series start year was not the same for every country. Our ideology was to fit the data to models that varied in their level of complexity. So, in addition to simpler methods of forecasting, we also used state of the art algorithms that searches from hundreds and thousands of models to return the model that captures the maximum information, rendering a superior fit for better predictions. We applied these models individually across all product categories across all countries.

To briefly outline the fitting and forecasting process, we start off by fitting the data with various models (by estimating relevant model parameters).We then check for the validity of the fit by checking the assumptions – such as the ACF of white noise and correlation between error terms. Finally we produce forecasts from each model applied to each product category across all countries. The model which was most consistent with the original series and had more superior predictions was finally chosen as the best model.In the next section, we briefly lay out the intuition behind these forecasting techniques and why we choose them.

The **naïve** method is the simplest method of forecasting we used. Typically used for data with smaller sizes, the naïve method forecasts by simply using the average of the time series data where every data point in the time series gets equal weights. This method is surprisingly effective for smaller data sets that does not have complicated trends and seasons. A more refined naive method for capturing the seasonal effects is the **seasonal naïve** method which divides the forecasts into separate seasons based on value of seasonality. The next model in our increasing level of complexity is the **linear model**. The linear model is also called a multiple regression model. Time series data can be broken down into three components – trend, season and cycles. The idea of using a

linear model is to use the trend and the seasonal component as predictor variables. Much like multiple regression, this technique uses least squared error of the predicted versus the actual data to fit the model to the data. The linear model, like the naïve is also surprisingly effective on short data sets due to their simplicity.
The **ARIMA** method is probably the most frequently used technique used to fit and forecast univariate time series model. What makes ARIMA so effective is an autoregressive (a regression of past error terms) component and a moving average (a time shifting average of past data points) component can be integrated into one model to capture the intricate seasons and trends underlying the actual data. Another distinguishing feature of these models is that they have separate seasonal and non seasonal components allowing a general framework to capture different types of processes.Finally the most advanced model we used were **Exponential Smoothening Using State Space**. Exponential smoothening by itself is a simple technique where more weights are placed on more recent observation because they are more important in developing forecasts. Over the years there have been more modifications to this simple model allowing for trend (Holt's method) and seasonality (The Holt-Winters method). This framework was further extended by allowing for additive or multiplicative trends. The ETS (or Error-Trend-Season) model is an umbrella term that is used for the various *states* or components that can be combined to fit a model based on its unique features. The ETS models are sometimes more accurate than ARIMA models and are effective on time series of varying lengths. The feature of ARIMA and the ETS that makes it readily applicable is that an information criteria (such as AIC or the BIC) can be used to select the best models. This information criterion also makes it possible to search from thousands of models to select the optimal one.

3.2 Validating the Forecast:

Traditional methods of validating forecasts dictate the use of a train-test split. The train set would be used to train the model to optimize fit and then test or validate the effectiveness of the model using a test set. Given that we had only 52 data points a train test split would make our model extremely unstable and provide poor forecasts. Therefore, we used **time series cross validation** to validate our models and find the best fit. The time series cross validation like traditional cross validation, splits the data into multiple different smaller test sets. The error is then calculated for each of these smaller sets and averaged in the end to give the final measure of error. We were able to extract the error and calculate the RMSE. These error measures were recorded for every model applied to every product across all nations. The model with the lowest RMSE was chosen as the best model.

3.3 Framework for Segmentation:

For segmenting customers, we chose to segment using countries as customers instead of using individual customers within each country. The absence of sufficient covariates provided hindrance from using tradition statistical methods of segmentation. The framework for segmenting products and customers (countries) was borrowed from the infamous BCG matrix – a segmentation framework originally proposed to segment brands. We modified the framework and created a segmentation plan to segment the products within each country and customers (countries) within each product category. Like the BCG matrix we used growth (of the product or customer) on the y-axis and the relative proportion of sales volume of each product category within a country (for segmenting products) or sales volume of from each customer within a product category (for segmenting customers) on the x-axis to visualize the position of the product or customer. We added another layer to the product or customer by sizing them by the total number of orders. This would capture the product or customer which had higher proportion of sales but lower number of orders. Finally we added a fourth dimension - time. We extracted these numbers for every quarter of the given years. This allowed for a richer and more in depth insight into how the segments are changing over time.

4 Results:

In this section, we provide the results of the models used and detailed findings. We also segment countries and products and provide recommendations.

4.1 Time Series Model Selection:

With the multiple model approach, we can select the best model based on several criteria. We selected the best model based on root mean squared error (RMSE). RMSE is a standard measure of the square root of the average of the squared difference between the actual point and the forecast model. We made our model decisions by minimizing the RMSE. The error diagnostics are performed on the residuals – the value of the difference between the model and the actual fitted data before the forecast area. The should not be any correlation in the residuals - indicated by the ACF peaks not being above the significance line, the residuals should also be normally distributed, and finally the residuals must also pass the Ljung box test which tests the hypothesis of correlation.

Results

	Product	Model Selection		Diagnostic Tests			Point Forecast			
		Model	RMSE	ACF	Normality	Ljung-Box Test	May	June	July	August
Bielize North East	Beer	Arima	5376.573	✓	✓	✓	11447.57	11447.57	11447.57	11447.57
	Food	Linear	774.2937	✓	✓	×	3049.98	2283.106	2075.755	2306.941
	NAB	Arima	1226.779	✓	✓	✓	2405.551	2405.551	2405.551	2405.551
	Spirits	Linear	1634.461	✓	✓	×	4792.731	3722.889	4406.351	5770.637
	Wine	Naïve	557.833	✓	✓	✓	320.3109	377.0573	715.2715	1307.0178
Bielize South East	Beer	Naïve	10117.65	✓	✓	✓	24599.34	30265.43	28701.45	31648.01
	Food	Arima	2493.779	✓	✓	✓	17511.76	17193.58	15373.36	19380.71
	NAB	ets	4123.941	✓	✓	✓	10930.76	10930.76	10930.76	10930.76
	RTDFAB	Linear	1666.844	✓	✓	×	757.4647	528.5839	1567.5154	2297.8253
	Spirits	Linear	2199.551	✓	✓	×	11236.88	10602.41	12428.37	12564.08
	Wine	Linear	2484.679	✓	✓	×	6251.619	8070.226	11103.109	14347.078
Congo	Beer	Linear	9511.282	×	✓	×	6961.842	6961.842	6961.842	6961.842
	Food	Arima	2371.601	✓	✓	✓	6084.026	6186.783	6587.373	6618.856
	NAB	Naïve	3614.202	×	✓	×	17996.83	13571.33	13179	20004.28
	Spirits	Linear	2245.088	✓	✓	✓	8460.349	7265.289	9359.297	11893.737
Finland	Beer	Naïve	7434.584	×	×	×	18448.94	11001.74	10976.06	15271.04
	Food	ets	855.8638	×	✓	×	16610.23	21696.29	18929.46	17220.37
	NAB	Arima	3185.09	×	✓	✓	21932.84	21477.67	21021.49	18105.17
	Spirits	Linear	2780.623	✓	✓	✓	18182.31	19587.22	20440.54	15139.23
India	Beer	Naïve	11350.29	×	✓	×	6259.50	6280.90	9741.28	5756.60
	Food	Linear	3793.67	×	✓	×	23946.50	30674.12	45113.24	46629.96
	NAB	Linear	4847.73	×	✓	✓	41185.90	40655.72	42003.38	35328.72
	RTD/FAB	Naïve	1832.50	×	✓	×	11093.76	8647.74	12198.00	8549.30
	Spirits	Linear	1656.51	✓	✓	✓	5576.10	6907.72	8375.22	2299.23
	Wine	Linear	6800.32	✓	✓	×	135763.17	133681.49	144261.65	80746.98
Uganda	Beer	Linear	15748.58	✓	✓	✓	278279.80	285176.40	282221.50	272884.30
	Drug	ets	469.65	✓	✓	✓	1537.76	1537.76	1537.76	1537.76
	Food	Linear	6530.53	✓	✓	✓	65743.22	62333.19	74518.38	79929.03
	NAB	Linear	6563.01	×	✓	✓	59021.51	58346.47	49402.97	51731.37
	RTD/FAB	Linear	3549.06	✓	✓	✓	10974.73	13402.72	14053.82	12010.75
	Spirits	Naïve	3802.68	✓	✓	✓	33488.24	36854.07	31858.48	40125.33
	Unknown	ets	7386.62	✓	✓	✓	29610.83	29610.83	29610.83	29610.83
	Wine	Linear	6666.20	✓	✓	✓	62764.52	61610.06	54051.23	56690.37

Time series model selection

Each product of each country is listed in the table above with the best model and the selection criterion. The diagnostic tests show any warnings of autocorrelation in residuals. The tests should not be treated as an excluding factor for a model. In fact it is uncommon for a model to pass all diagnostic checks and have desirable error rates in real life scenarios. Obviously the checks indicate that the model passed the test. Included with each product is the best model forecast for May, June, July and August. Also included in the appendix are the forecast visuals for each country on all the methods listed above. Section 6.2 show all the forecasts for India for all the product categories. Similarly section 6.3, section 6.5, section 6.4, section 6.6 and section 6.7 shows the forecasts for Uganda, Finland, Congo, North-East Belieze and South-East Belieze respectively. The HTML files accompanying this report has all the visuals for all the test performed on every product across every country.

4.2 Comparison with OI Forecast:

It is **statistically unrealistic** to use the volume from 24 months to forecast the next 24 months. There are not enough data points to build a model. An attempt lead to unstable forecasts with extremely wide confidence intervals. Since one of the objectives of the competition was to compare the OI forecasts to our forecasts, the solution was to use all data points up to the end of 2016 and forecast the next three. This would give us a chance to compare both forecasts relatively fairly. Please note it is still unclear how many months (or years) of data OI has used to create the forecast column in the dataset. Also, given the fact the we only had 52 months (for most countries) our forecasts did prove to be inferior for some categories. But, we are confident that if the time frame to model the data was longer, our models would perform significantly better than OI forecasts. *Therefore, the results of forecast comparison* ***was not*** *used to for building and reporting the models that we think are best given the data we had.* The visuals associated with each country-wise forecast comparison is linked to the name of the country. The visuals are also present in the HTML files accompanying this report. The following is the summary of the forecast comparison by country.

India [6.10]**:**The OI forecast is the lowest RMSE for Beer. For Food, the ets and linear models are very close as the lowest RMSE. NAB and Spirits have the OI forecast as the lowest RMSE. For RTDFAB and Wine, linear and ets are slightly lower than the OI forecast.

Uganda [6.11]**:** The linear model was the lowest RMSE for Beer and Drug and Chemical. The OI forecast RMSE was not close for these product categories. Food and NAB had the lowest RMSE in the OI forecast and those values were close to other models we used. RTDFAB was significantly better for the OI forecast. The linear model was the lowest RMSE for Spirits. The OI forecast and the linear model were very close for Wine.

Congo [6.12]**:** The RMSE for the OI forecast for Beer was much lower than our best model RMSE. The OI forecast may have benefited from more data to generate the forecast. The linear model was the best model for Drug and Chemical; there was missing data for this category and there were difficulties with forecasting. The OI forecast had a lower RMSE for Food. NAB, Spirits and Wine were best modeled by our forecast models.

Finland [6.13]**:** The OI forecast RMSE was much lower in Finland for Beer as well. The model that has the lowest RMSE for Food was the Linear model. For Miscellaneous, the ets model was slightly lower than the OI forecast. The OI forecast had a lower RMSE for NAB. RTDFAB had a lower RMSE in the linear model but there was a shortage of data that may have skewed the results. The linear model for Spirits was very slightly better than the OI forecast. The linear model was also the best model for Wine.

North East Belize [6.14]**:** Beer is modeled best by the linear model. The OI forecast RMSE for Drug and Chemical is very low compared to the other models suggesting a well fit model. ETS and linear are very close for Food and the OI forecast RMSE is very large. NAB, RTDFAB and Spirits have lower RMSE in the linear models. Wine has a much lower RMSE in the OI forecast.

South East Belize [6.15]**:** The linear forecast has the lowest RMSE for Beer. There was not enough data for Drug and Chemical to be able to compare forecasts easily. Food and Wine was best modeled by the OI forecast by a larger margin. NAB, RTDFAB, Spirits and Unknown selected linear as the model that minimized RMSE. These models also were selected by a large margin over the OI forecast.

4.3 Segmentation

We split the segmentation into two parts - segmentation of products and customers. As pointed out earlier, we considered the countries to be customers within a product category to make our recommendations more interpretable.

4.3.1 Segmenting Products

The final task was to segment the customers and provide guidance on business decisions on each segment. Many decisions regarding products involve extrinsic factors such as margin per unit that were not available to us. Our decisions focus on the growth rate of products within the business units. Information regarding quarterly growth rates is charted in the appendix.

India[64]: Q1 shows mixed results with Q2 providing most of the yearly growth. Q4 shows declines in all categories but Wine. As a business unit, Q4 has some of the worst declines throughout the year. The focus of India should be Q4 and building the categories that show the worst rates. Wine dominates over 75% of the number of orders but only slightly higher than 50% of the volume. Wine shows alternating growth through each quarter of the data provided. Quarters 2 and 4 show growth while quarters 1 and 3 show decline. Focusing on decreasing the losses in Q1 and Q3 will help stabilize Wine since it is such a large volume. Food occupies the second highest number of orders but the third highest volume. In the last 2 years of data, Food has horrible results in Q1 but rebounds sharply in Q2 before tapering off in Q3 and Q4. Focusing on Q1 and the causes may help increase total volume for Food. Non-Alcoholic Beverage is the second highest volume with the third highest number of orders. The ratio suggests that major bottlers are ordering a higher volume per shipment. Q1 and Q2 show growth followed by losses in Q3 and Q4. The decline rate is much worse than the recovering growth rate in Q1 and Q2 so this product category may need focus to help alleviate some of the losses. Spirits are such a low percentage of volume and number of orders that unless there is a specific business reason to focus on the segment, Spirits should not receive the attention that Wine, Food and Non-alcoholic Beverage receive.

Uganda[65]: Across all products, Q1 shows modest growth with much of the yearly growth coming in Q2 before slowing down into Q3 and Q4. Q4 appears to concentrate the losses. As a business unit, Uganda needs to focus on lessening the effect of Q4 on the yearly totals. Beer dominates the highest segment of volume and number of orders. Beer shows modest growth and decline. Seasonally, Q1 and Q2 model growth and Q3 and Q4 decline. This section is stable but should be monitored due to the high volume. Food occupies approximately 13% of the total volume of Uganda. Food has shown a gain in Q3 and losses in the other quarters. This is alarming because of the volume that Food occupies. Special attention should be granted to help stabilize the category. Wine accounts for about 10% of the volume of Uganda shipments. Wine shows growth in Q1 and Q2 with decline in Q3 and Q4. The seasonality of Wine needs to be addressed and focused on the negative quarters.Non-Alcoholic Beverages are slightly lower than 10%. Non-Alcoholic Beverages do not seem to show much trend other than strong Q2. More information is needed to analyze for a business decision. Spirits occupy a lower proportion of volume but a higher percentage of sales. Spirits show growth in three quarters; only showing seasonal declines in Q4. Overall, Spirits appear stable, growing year over year.

Congo[66]: Throughout the data, Q4 shows promising growth. Q1 follows with moderate losses before larger growth in Q2 and lesser growth in Q3. Business focus should be on transitioning from Q4 volumes into Q1 to help normalize production. NAB and Beer are the largest and second largest by volume, respectively. Beer is approximately 2% of the total number of orders which signifies large orders. Through the data range, NAB is arguably the most stable product. Beer suffers from declining Q4 and Q1 before rapid growth in Q2 and Q3. Business decisions involving Beer need to be made with the seasonality and volume in mind. Spirits is the third largest volume and number of orders. Spirits show the most growth in Q3 and Q4 across the years. Because of the lower volume and orders, Spirits may not require the focus that Beer and Food necessitate. Food has a proportionally large number of orders to the fourth largest volume. Food is another very stable product. The stability of Food may be due to the large number of orders. Increasing the volume per shipment of Food should have a larger effect on growth rate than Beer or Spirits. RTD/FAB and Wine account for 3 orders. These segments should be ignored completely barring a complete change in the market.

Finland[67]: As a business unit, Finland shows very seasonal results. Over half the volume and number of orders are dominated by Wine. As a result, all business decisions should consider Wine, even if it is not the category in question. Wine occupies the highest volume and highest number of orders. Sharp gains in Q1 and Q2 are evened out by declines in Q3 and Q4. Business decisions should focus on increasing the growth rate in Q3 and Q4 while maintaining Q1 growth. Beer has the second highest volume with the second lowest number of orders. Beer has a sharp decline in growth rate in Q4. This decline may be overtaking the gains in Q2. Special focus should be spent on trying to improve the overall growth rate before this category loses most of the yearly volume.Non-Alcoholic Beverage is slightly less than 10% of total volume but less than 2% of total orders. NAB shows consistent Q4 declines. Focus should first be on Q4 for Wine before NAB. Food has about 8% of the total volume and total number of orders. In the first couple years, Food showed Q4 declines but in the last half of the data set, Food has mostly held even. This segment requires minimal attention due to low volumes. RTDFAB is less than 1% of orders and volume. RTD/FAB occupies such a low portion of Finland that if there is not a clear path to increasing volume and orders, it should not be focused.

Belize North East[68]: The largest segments of Belize North East experience declines in Q1. Business decisions should focus on improving Q1 and stability throughout the year. Beer is the largest by volume and the second largest by order. Beer experiences decline in the first half of the year followed by growth in the second half. Most of the decline is in Q1. With the high volume of Beer, focus should be on Q1 while maintaining Q3 growth. Food is the largest number of orders and the third largest volume. Food is relatively stable regarding growth rate and proportion of business across the data range. Food should require minimal focus. Spirits are a disproportionately large volume per number of orders. This segment should be focused on. With the current economy, there may be a chance to improve by finding new customers and new markets that have consumption like the modeled volume. Spirits volume grows in the second half after large declines in Q1 in each year. RTD/FAB are the smallest volume of orders. These categories should not be the focus unless there is a considerable market change.

Belize South East[69]: Growth and decline is mixed throughout the middle quarters with strong gains in Q4 followed by sharp declines in Q1. Further investigation should focus on Q1 while strengthening Q2 and Q3. Beer and Food are the largest categories by volume. The smaller number of orders suggests larger manufacturers ordering more Beer bottles per shipment. Beer experiences declines in Q1 and Q2 while growing rapidly in Q3 and Q4. Food is relatively stable. Beer should be focused on improving in Q1 and Q2. Non-Alcoholic Beverage and Spirits are the third and fourth largest categories by volume. NAB starts relatively stable but in the last half of the data, changes between growth and decline. Spirits show sharp declines in Q1 followed by 3 quarters of growth. Although Wine is one of the smaller proportions, Wine still occupies around 8% of the total volume. Wine fluctuates greatly between quarters. Wine needs investigated to find the cause of the wide variation in growth rate. RTD/FAB is the smallest proportion of volume and sales. RTD/FAB should not receive any extra attention barring market change or other incentives.

4.3.2 Segmenting Customers

General trends: It might be useful to talk about the general trends before looking at each customer within a product.Uganda is the largest volume country, followed by Finland and India. Uganda follows a seasonal trend with growth in Q2 and declining in Q4. Finland tends to sharply decline in Q3 and to a lesser extent in Q4 followed by a large growth in Q1 before leveling out in Q2. The overall rates for India are much less extreme than Finland but also follow a decline in Q4. Focus on India, Finland and Uganda should be on maintaining business strength from Q2 through Q4 to mitigate Q4 declines.South East Bielize follows a trend opposite of Finland. The strength of Q4 in South East Bielize is countered by declines in Q1. Congo grows in Q2-3 and declines in Q4-1. North East Bielize declines in Q1-2 and grows in Q3-4. However, due of the volume, South East Bielize, North East Bielize and Congo should not be given the same consideration as Finland, India and Uganda.

Beer [71]**:** The largest by volume product overall, Beer is vital to business. The largest manufacturer of Beer is Uganda. Seasonal trends exist similar to the overall trend with Q2 exhibiting growth and Q4 decline. South East Bielize shows very strong growth in Q4 as the second largest country by proportion

Wine [72]**:** India and Finland are the largest producers of Wine. India has much less variation in growth rate than Finland. Q1 growth in Finland is followed by lesser growth in Q2 and declines in Q3 and Q4.

Non Alcoholic Beverages [73]**:** Uganda is clearly the largest volume NAB producer with India behind. Uganda appears to be alternating growth and decline, with growth in Q2 and Q4. India is more seasonal, with Q2 as the top growth and Q4 as the largest decline.

Spirits [74]**:** Spirits shows a clear seasonal trend across all countries. Q1 shows sharp decline with Q2-4 rebounding before leveling off. Overall, Uganda still maintains the top volume in this category

RTDFAB [75]**:** Uganda and India dominate the volume with South East Bielize coming close in Q4. South East Bielize shows rapid growth in Q3 and Q4 to push close to Uganda and India. However, Q1 and Q2 are not strong for South East Bielize. The trend for Uganda is opposite the trend for South East Bielize.

Drug and Chemicals [76]**:** North East Bielize sharply declines after Q4 2015 and barely maintains a presence. Uganda and Congo are relatively stable, with occasional growth and decline.

Food [77]**:** Uganda dominates over 50% of this product category. There are very few sharp changes; evidence that Food is a stable product.

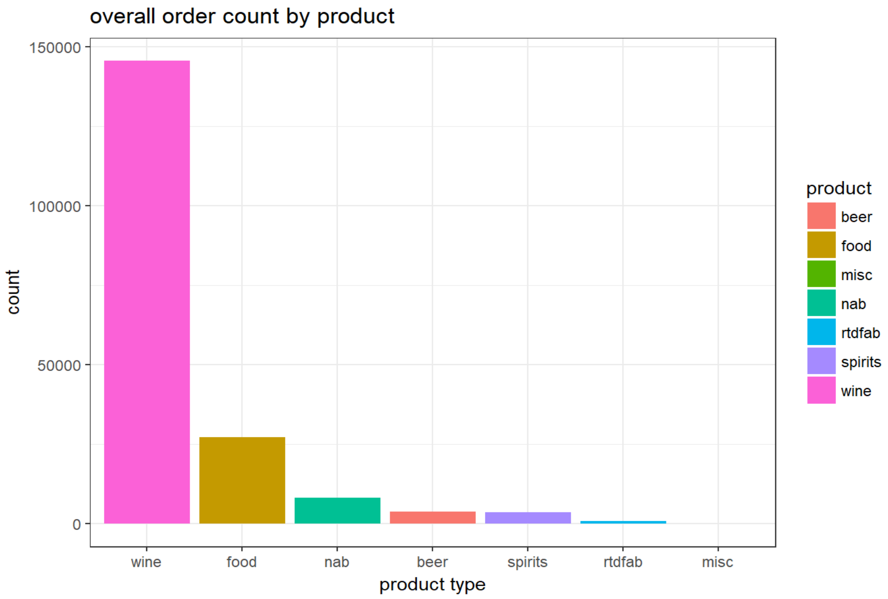
5 Conclusion

Difficulties arose forecasting using time series methods due to the insufficient length and missing data from the data set. The shorter length mandated cross-validation instead of the usual and more accurate training/test split. Using 24 data points to predict the following 24 points is statistically incorrect and will yield very inaccurate results. These results would be no better than an educated guess from an experienced manager. It is infeasible to compare the OI forecast accuracy to our model accuracy because the OI forecast time frame was from 2013-2016 and the competition forecast time frame was for May-August 2017. Also, The OI forecast may have included many more years of data which increased the forecast accuracy beyond the limitations of our best fit models. The window of forecast accuracy needed to be similar in length of data and months forecasted. Therefore, we modified the time frame to make the forecast comparison relatively fair.We were able to forecast almost every product type in every country. We understand that identifying the seasonal patterns and applying business principals to forecasting can increase profit and continued growth. This is why we used different techniques for every product for every country to ensure, the trend and seasons are captured correctly.

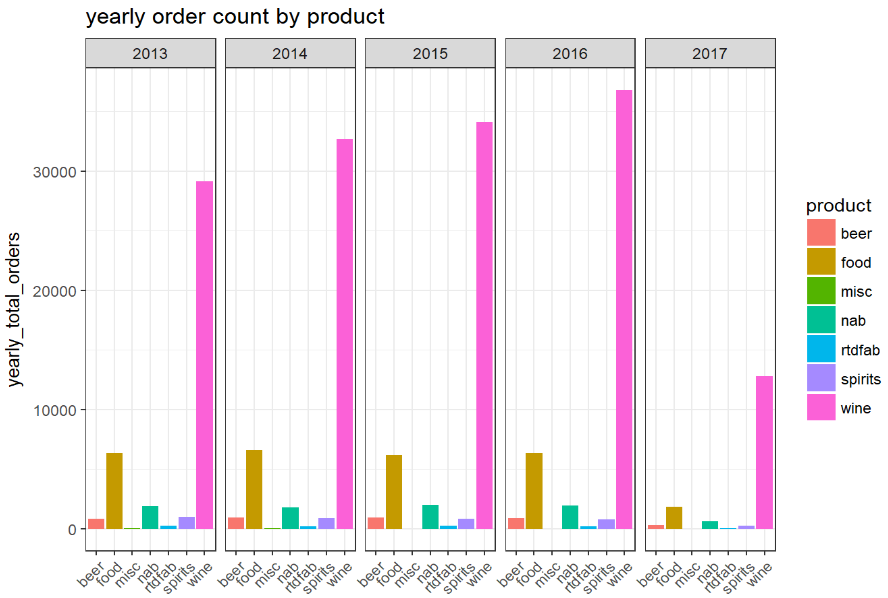
Calculating demand based on volume and number of orders is not ideal. Price and order size versus shipped size would have provided better variables to measure demand. We adapted and used growth rate and proportion of sales volume to accommodate the limited variables. Using a growth rate model for demand, we also suggest country based suggestions as well as product suggestions within the countries. Given more variables and a longer length of time series data, a much more accurate forecast can be provided. With the restrictions of the project, our models minimize RMSE and provide a realistic forecast for May-August 2017.

6 Appendix

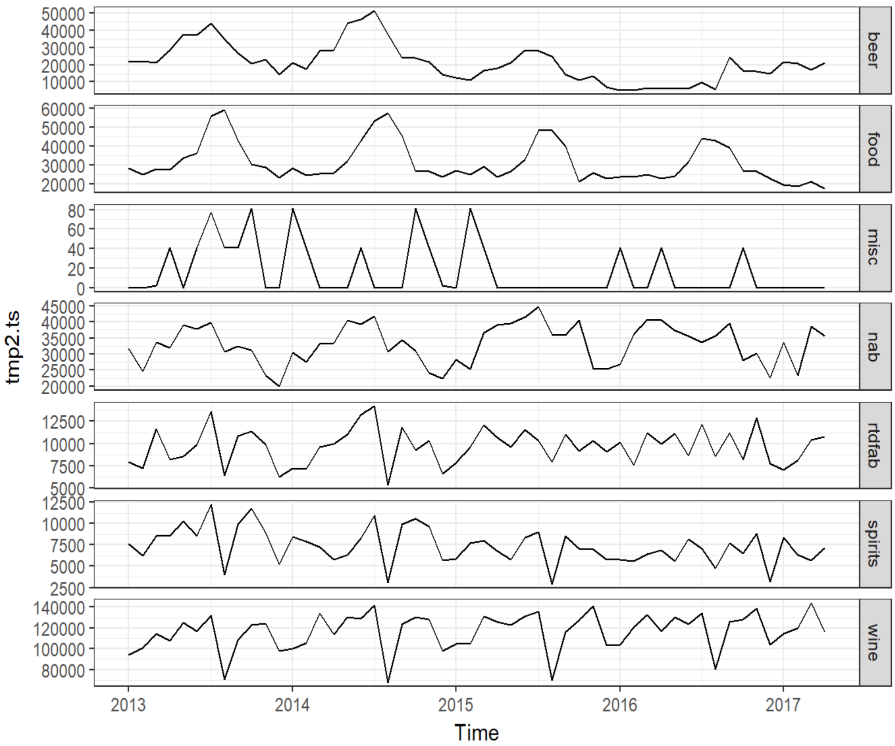
6.1 List of figures from EDA



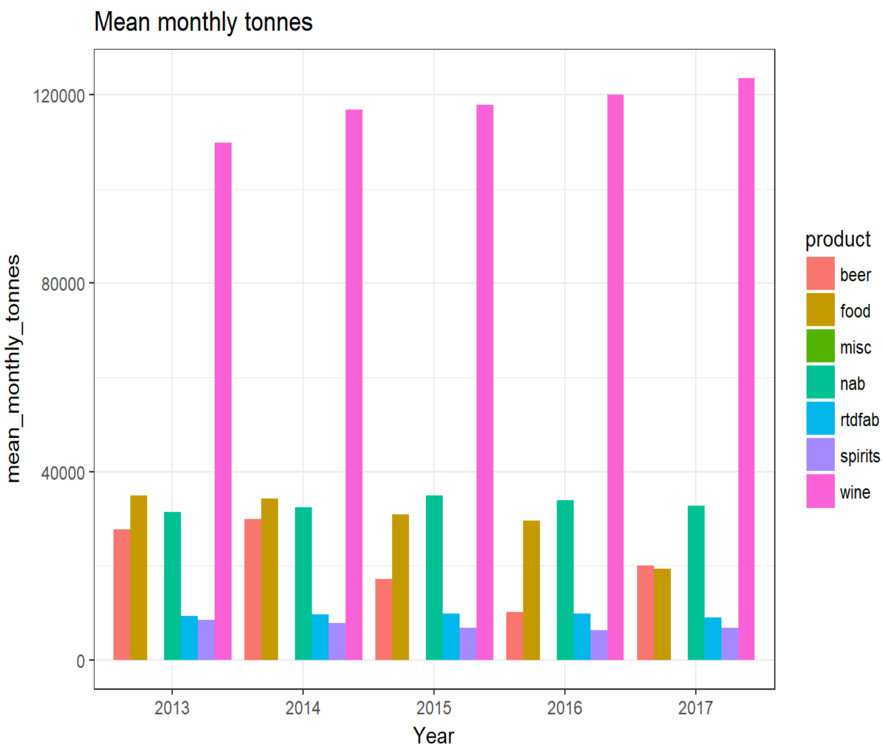
India category count



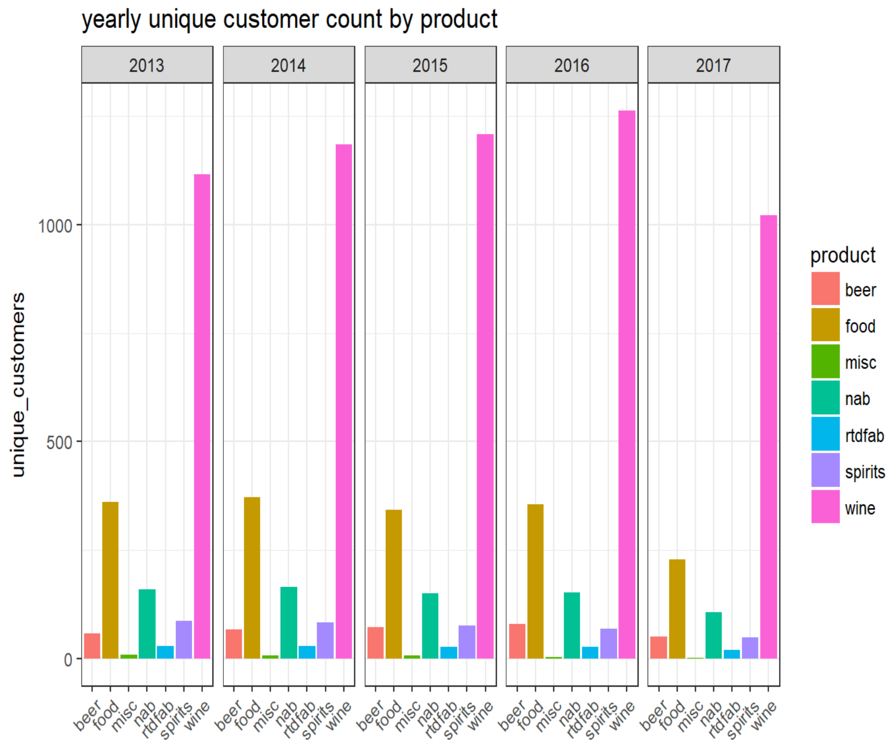
India annual category count



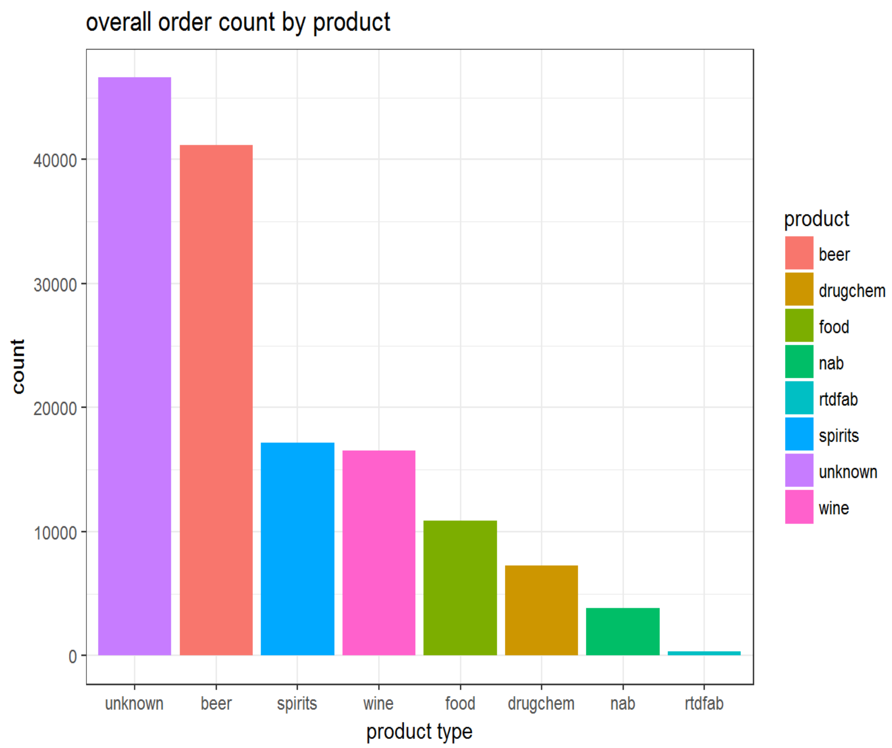
India Time Series



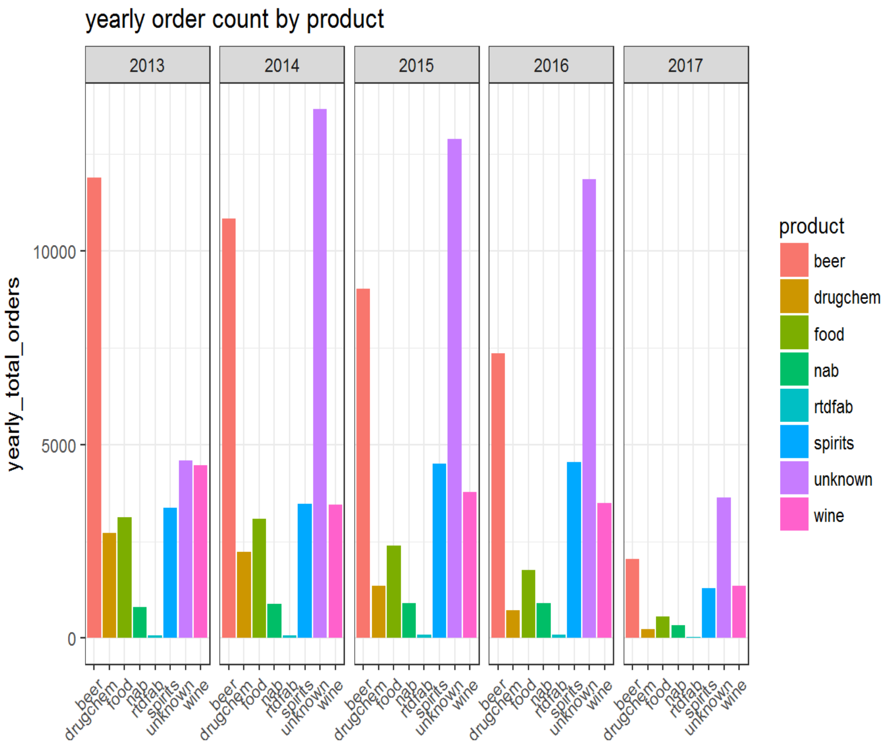
India annual mean tons shipped



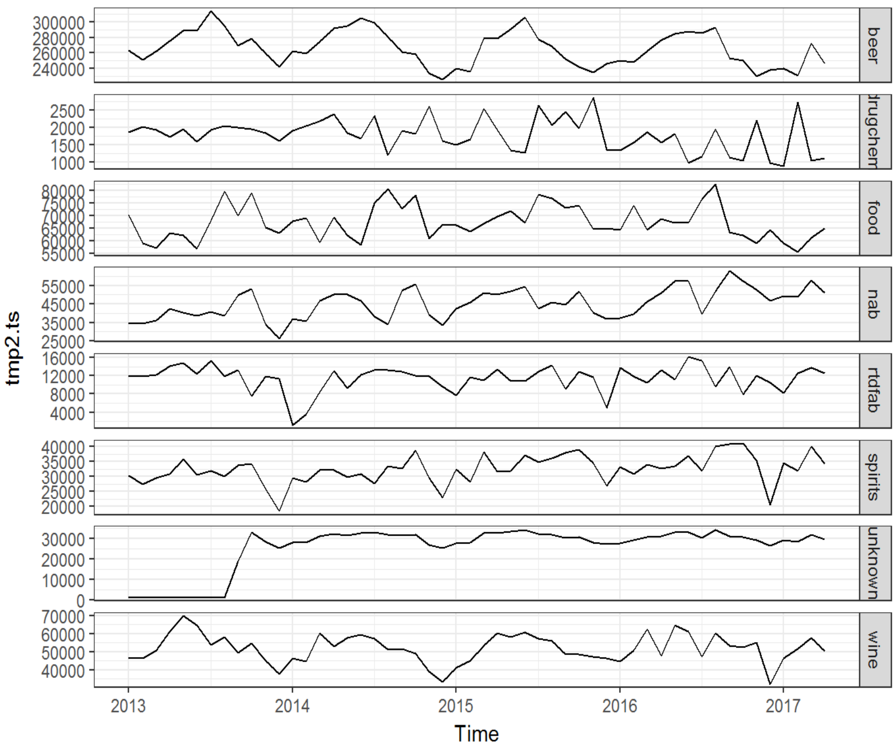
India unique customer count



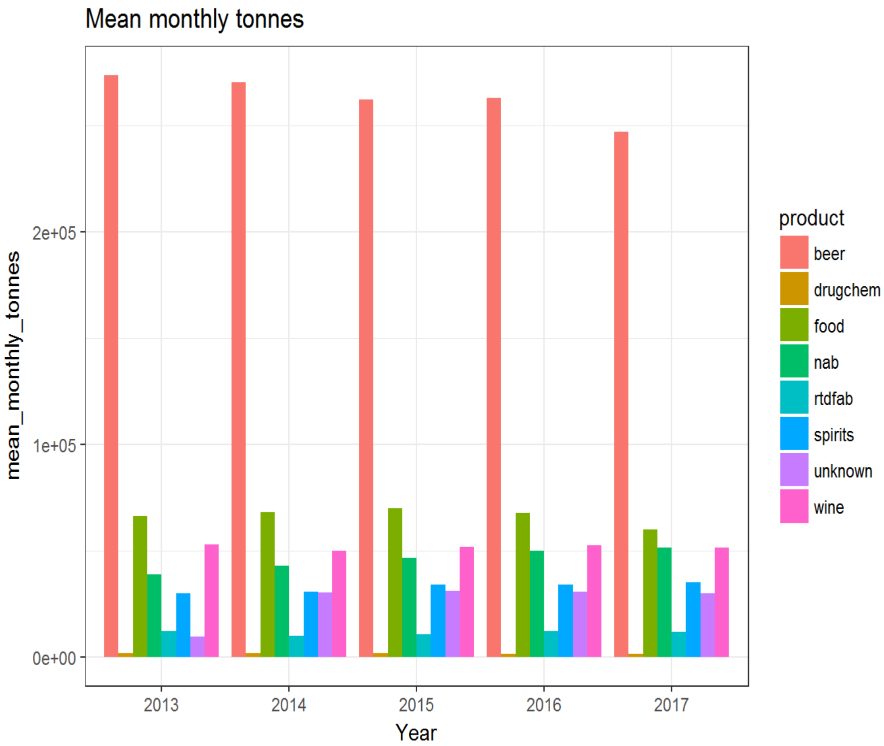
Uganda category count



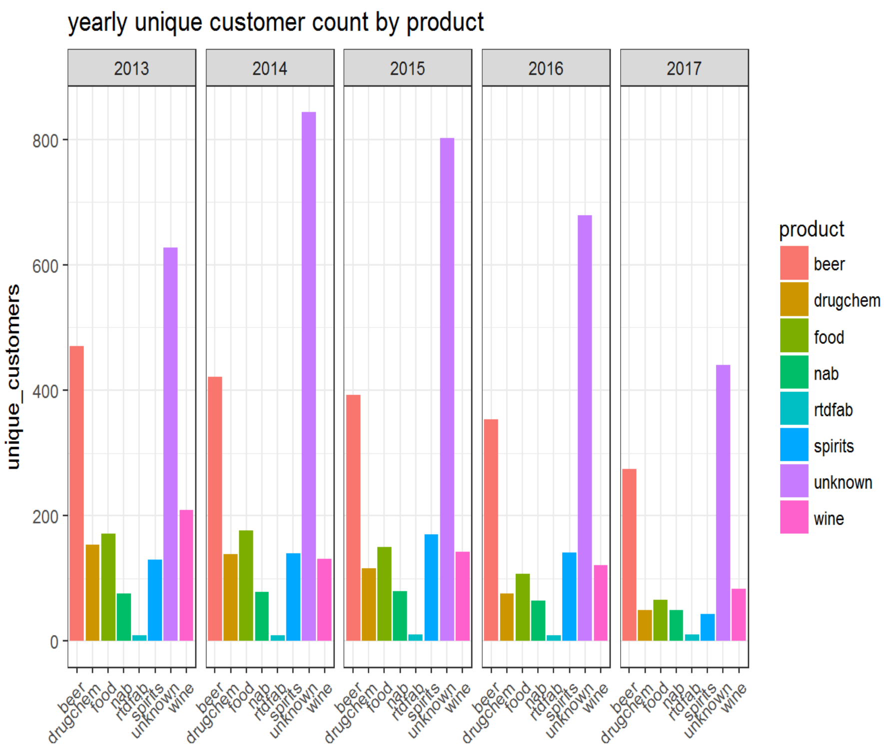
Uganda annual category count



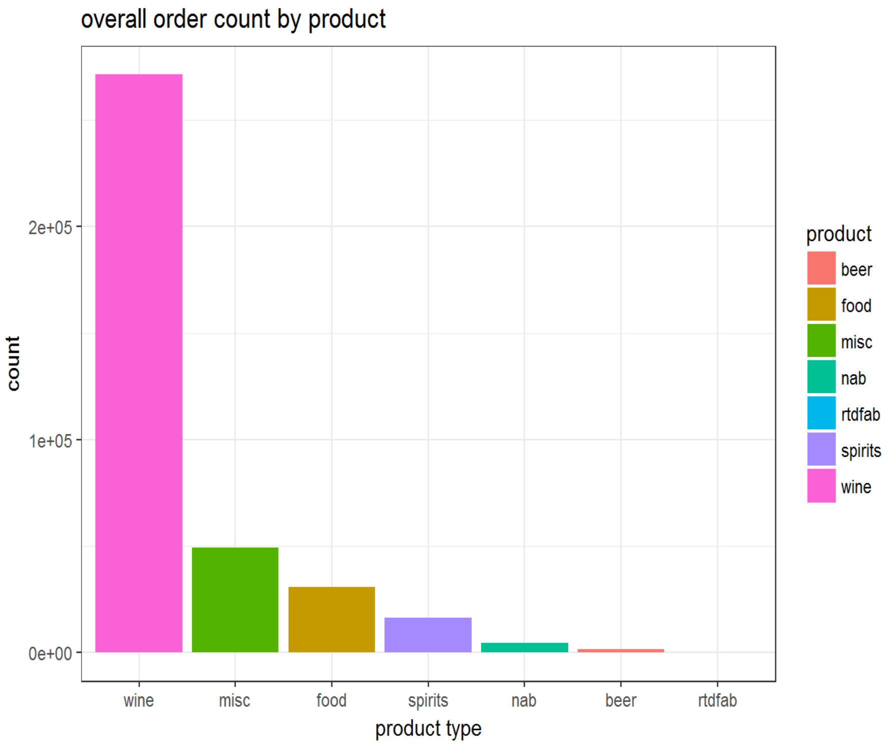
Uganda Time Series



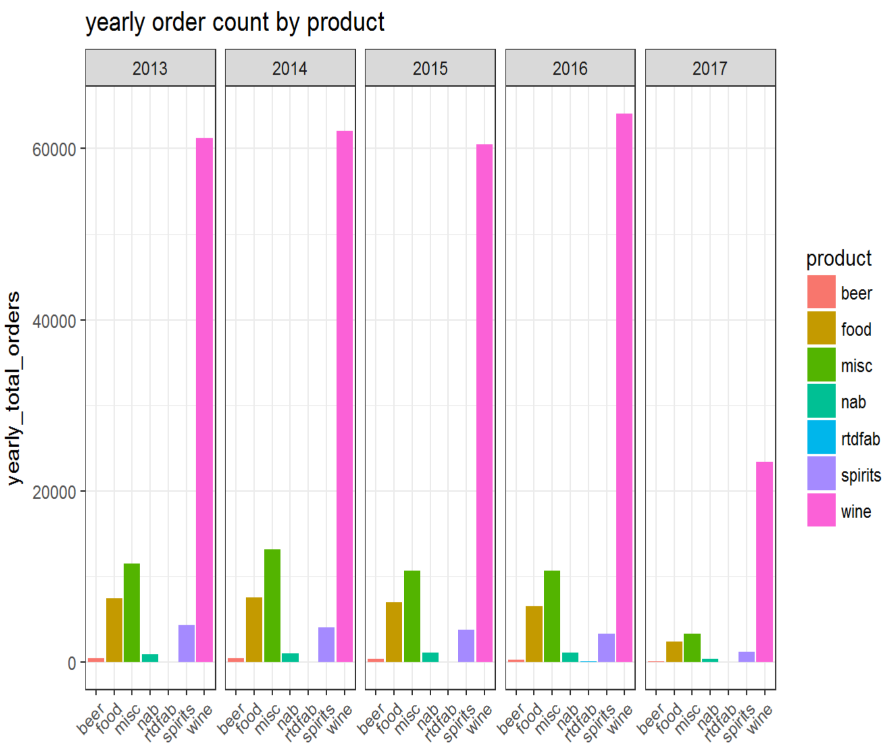
Uganda annual mean tons shipped



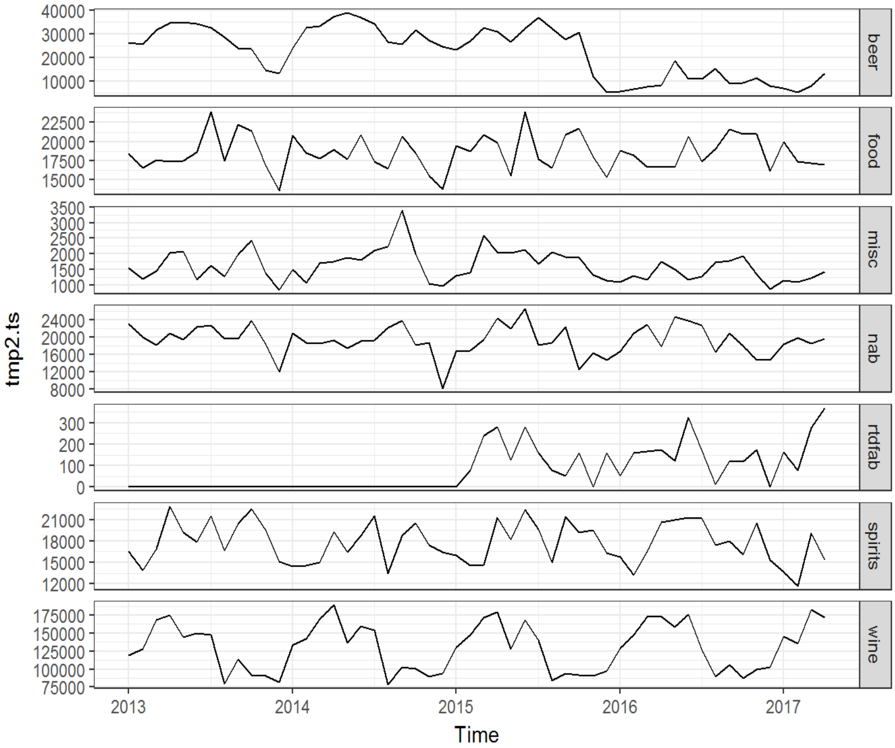
Uganda unique customer count



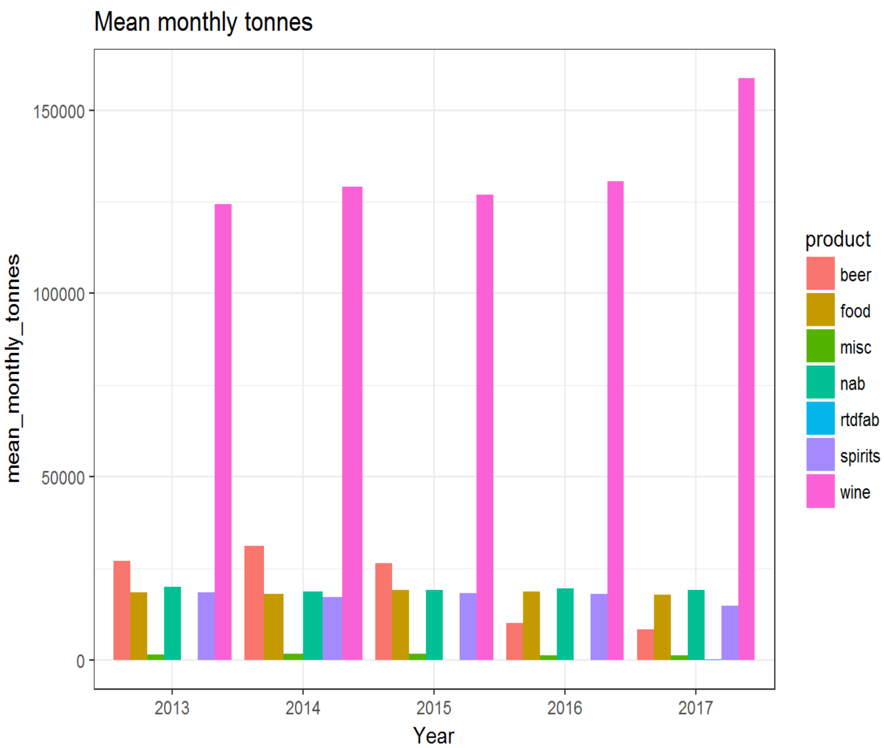
Finland category count



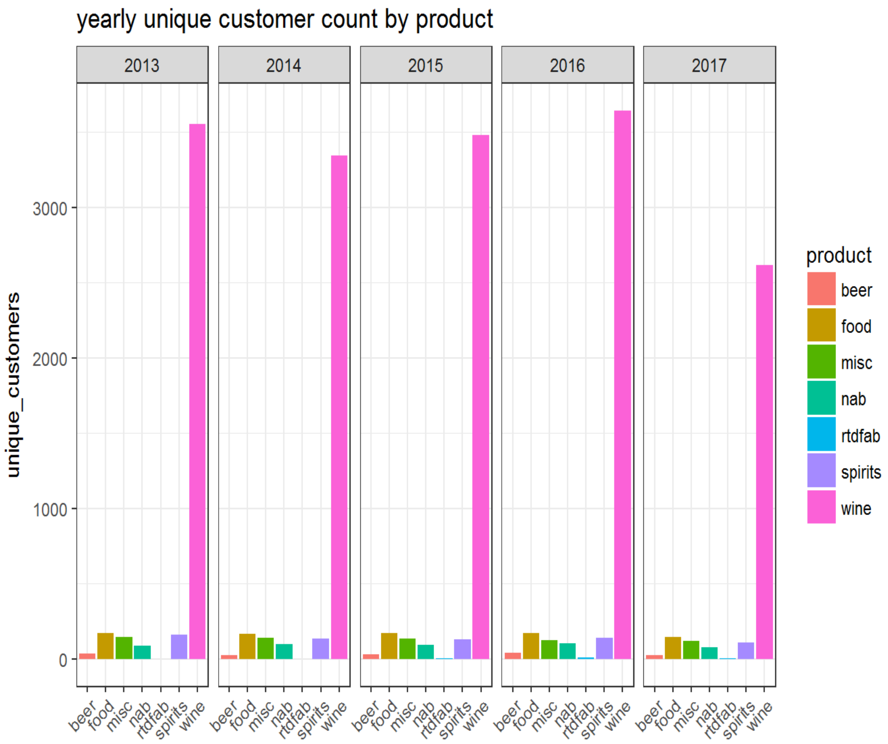
Finland annual category count



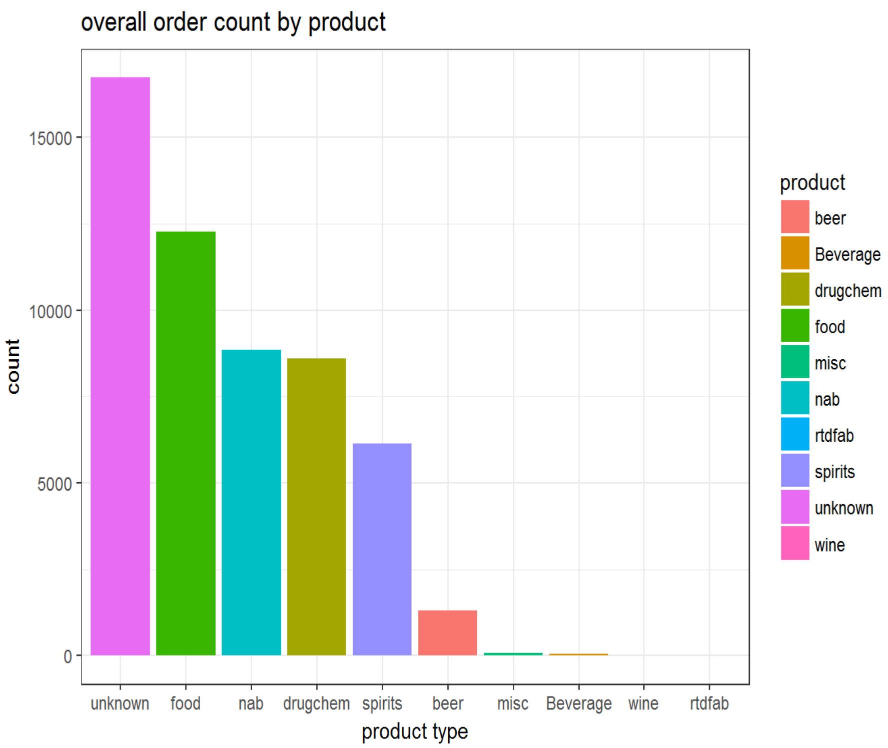
Finland Time Series



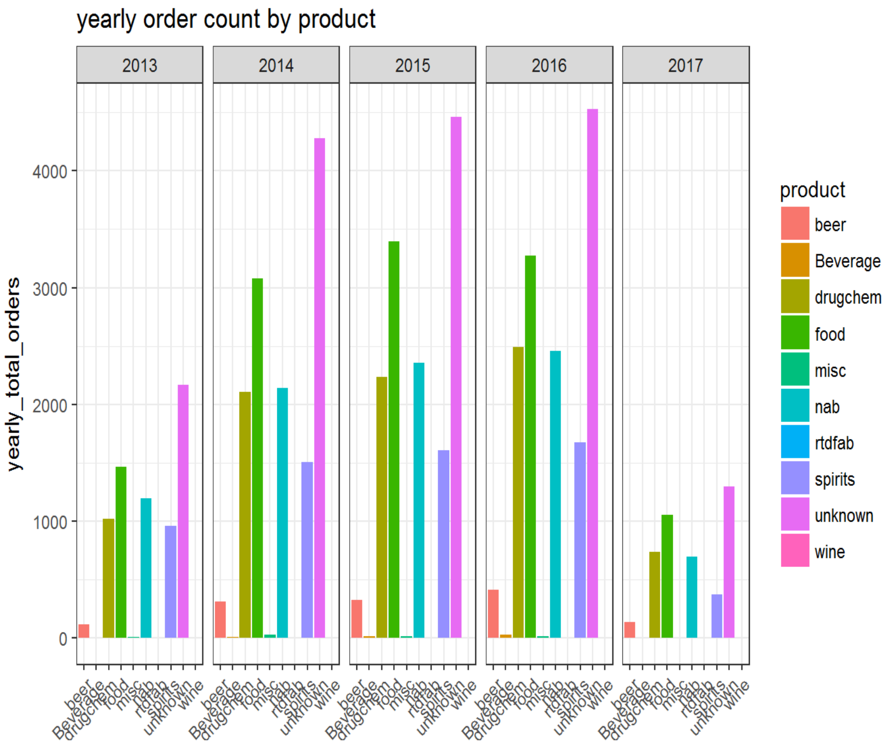
Finland annual mean tons shipped



Finland unique customer count



Congo category count



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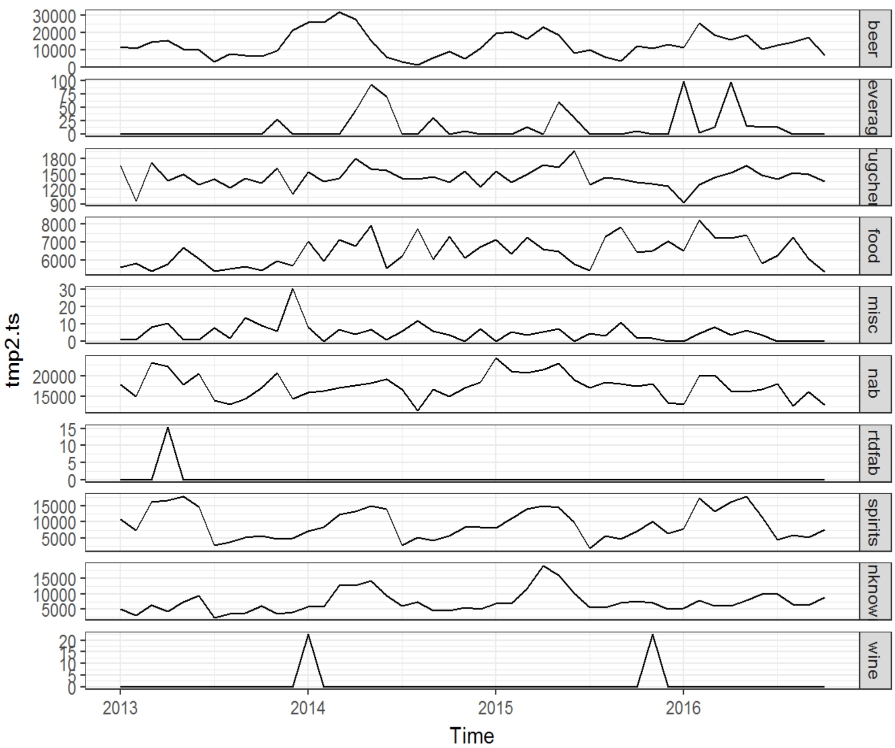

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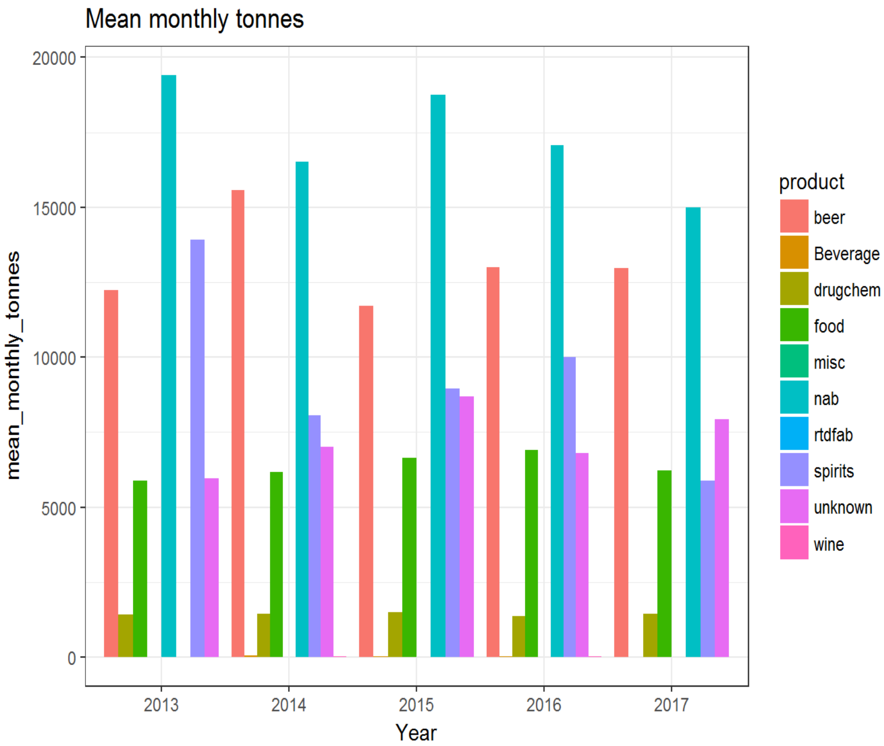
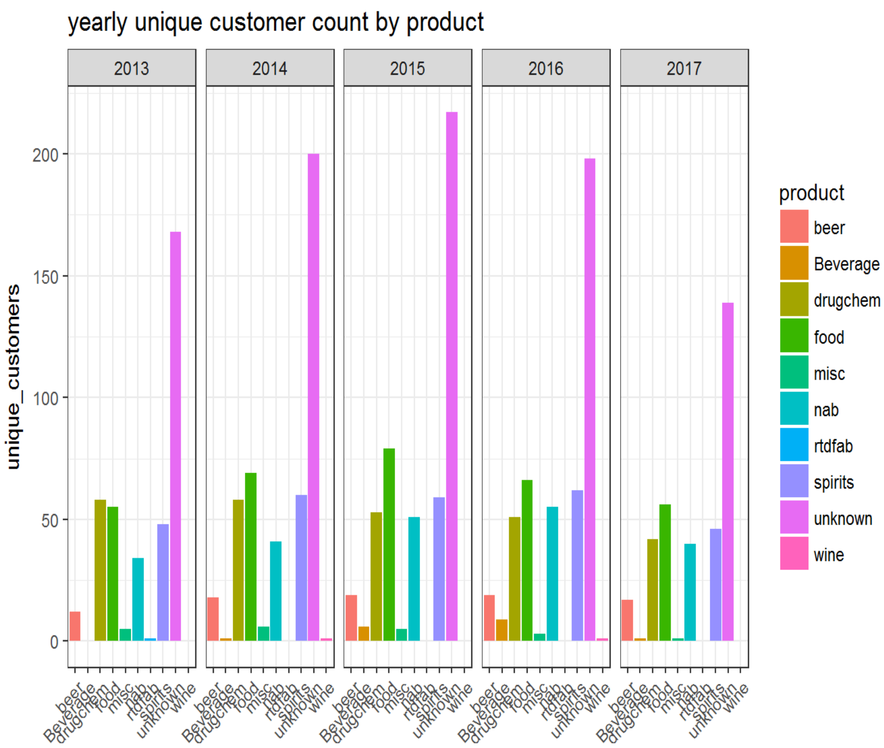


Congo annual mean tons shipped



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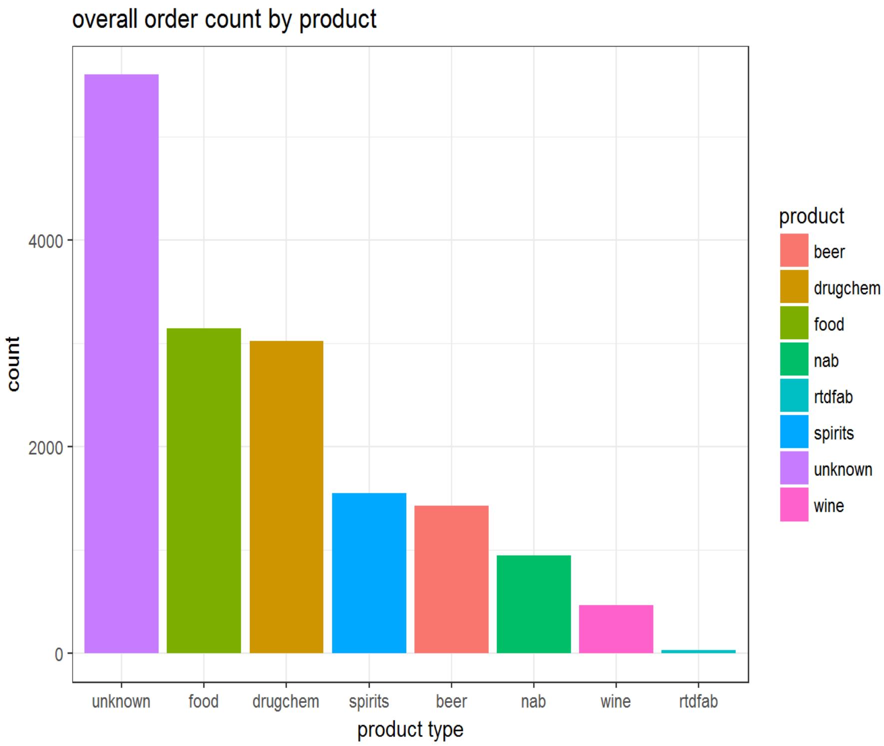
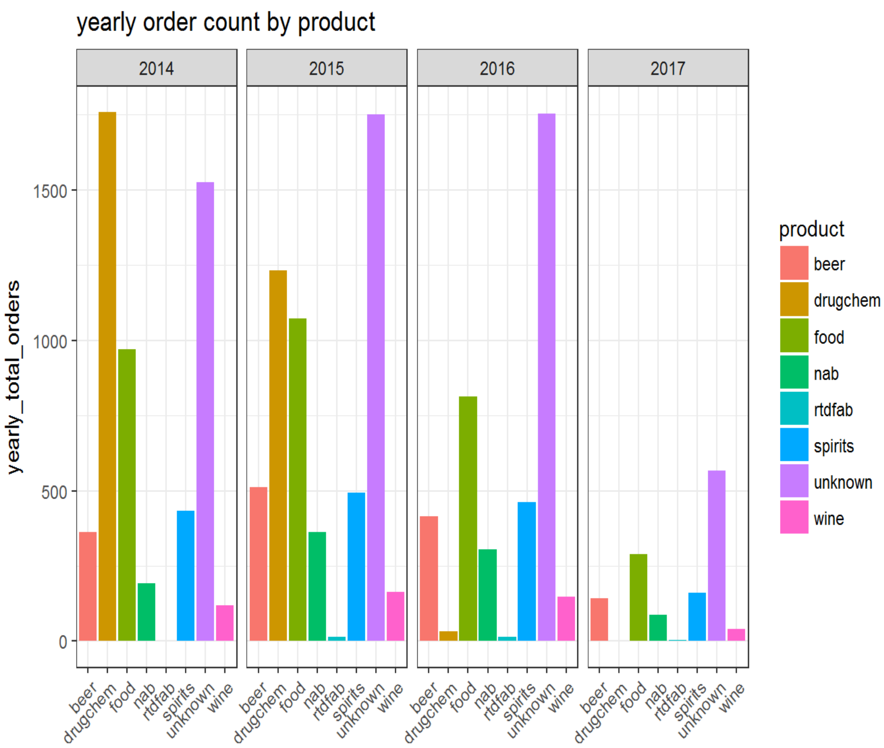


NE Belize category count



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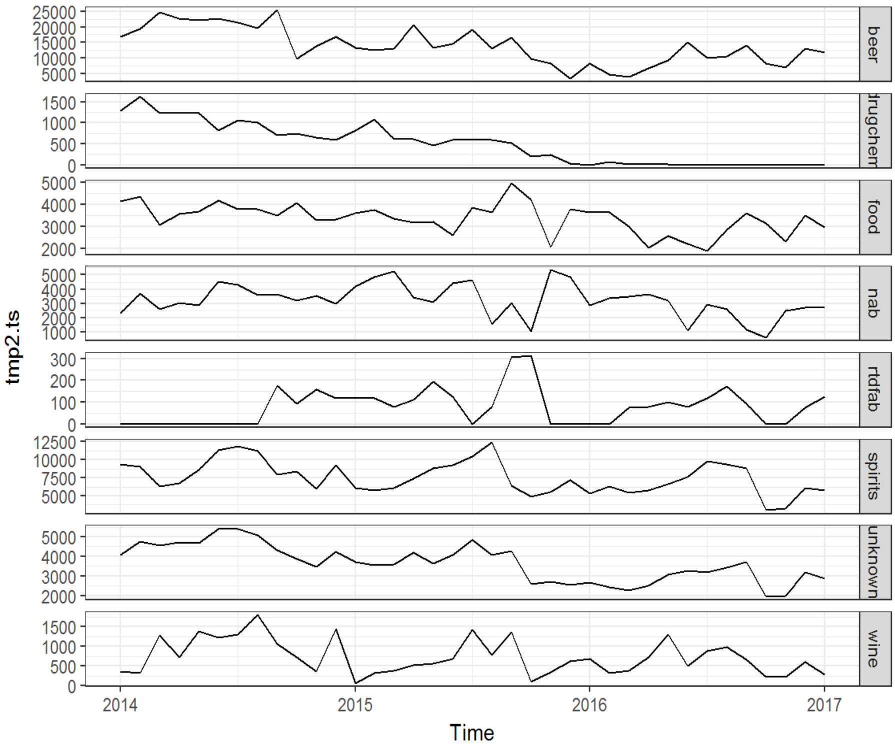
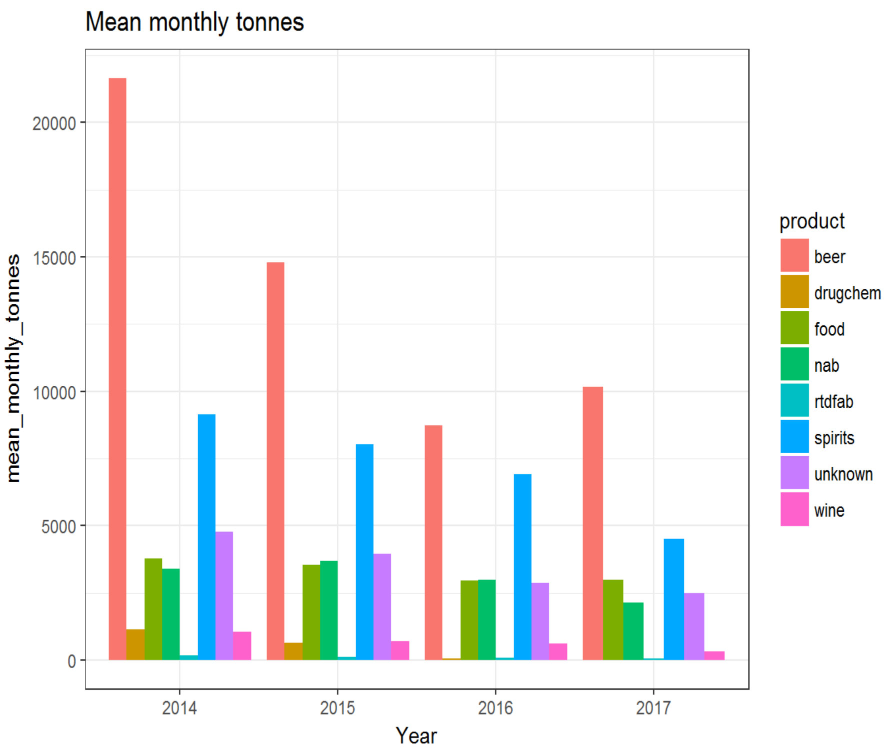
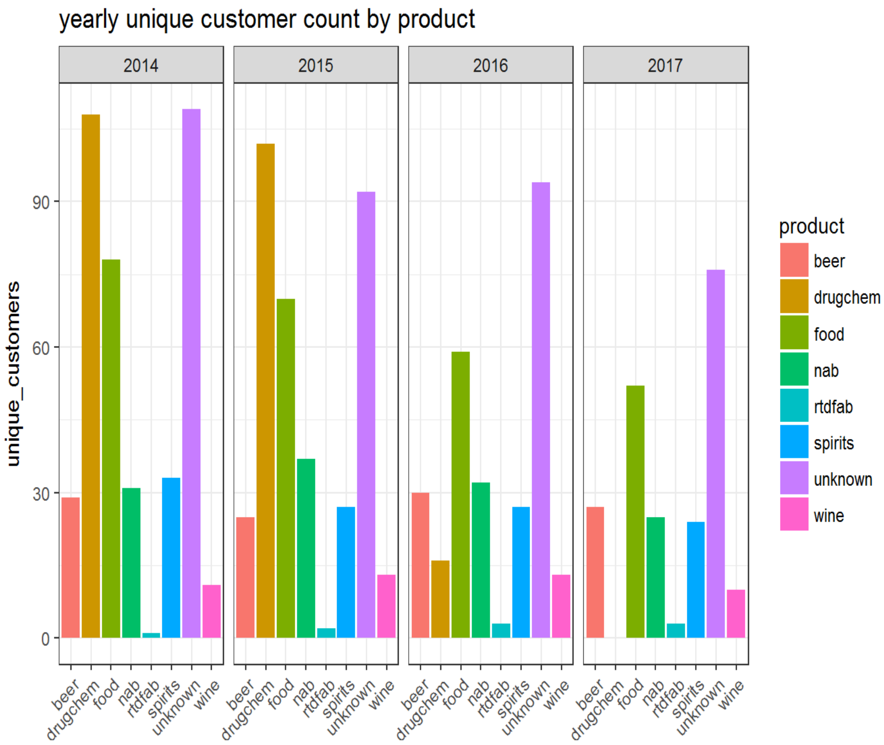


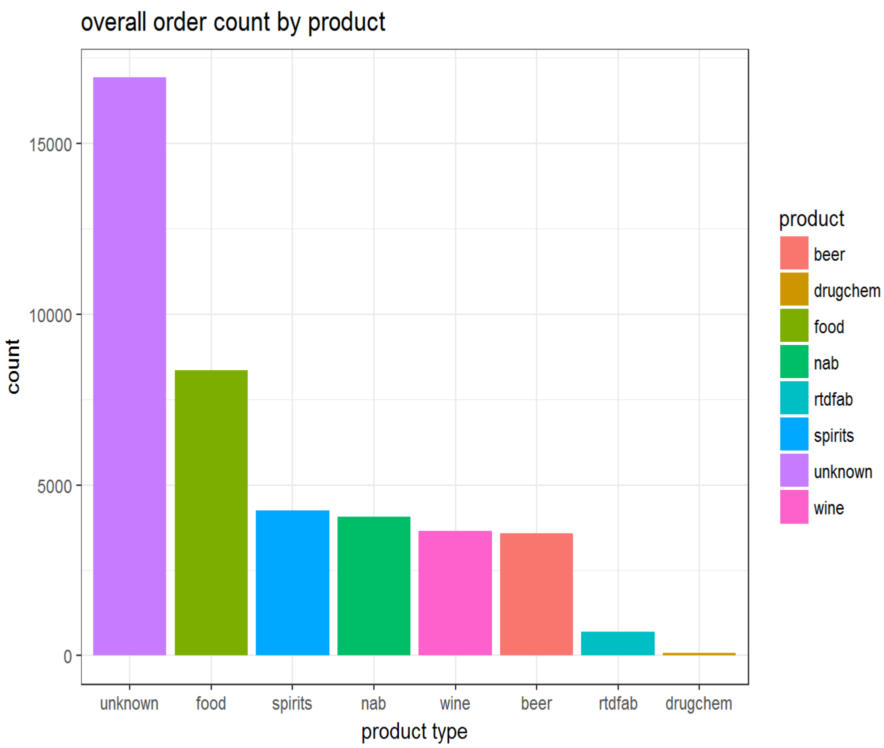
NE Belize Time Series



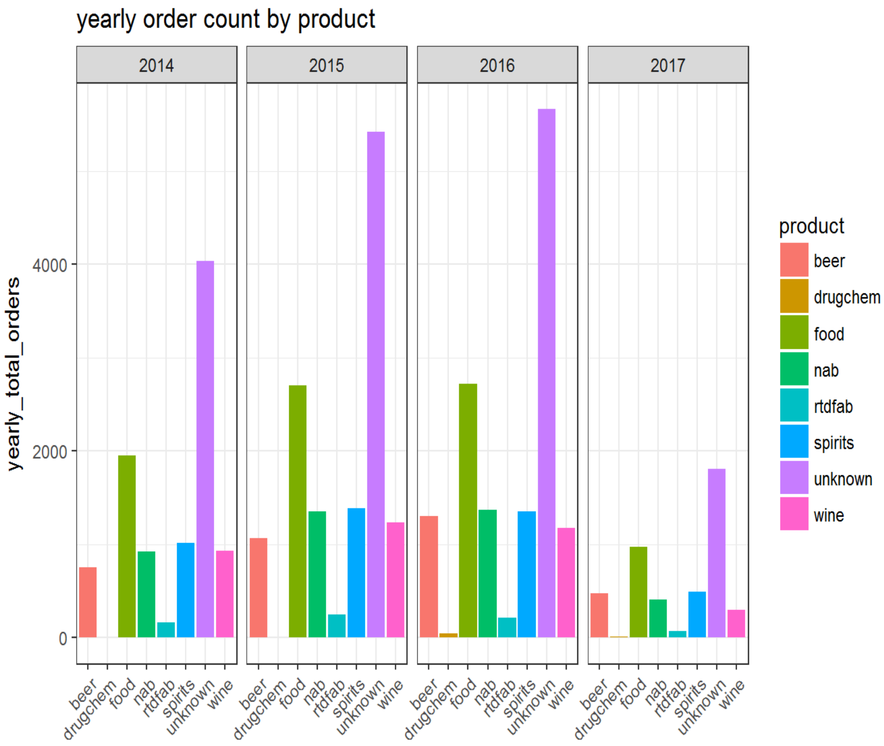
NE Belize annual mean tons shipped



NE Belize unique customer count



SE Belize category count



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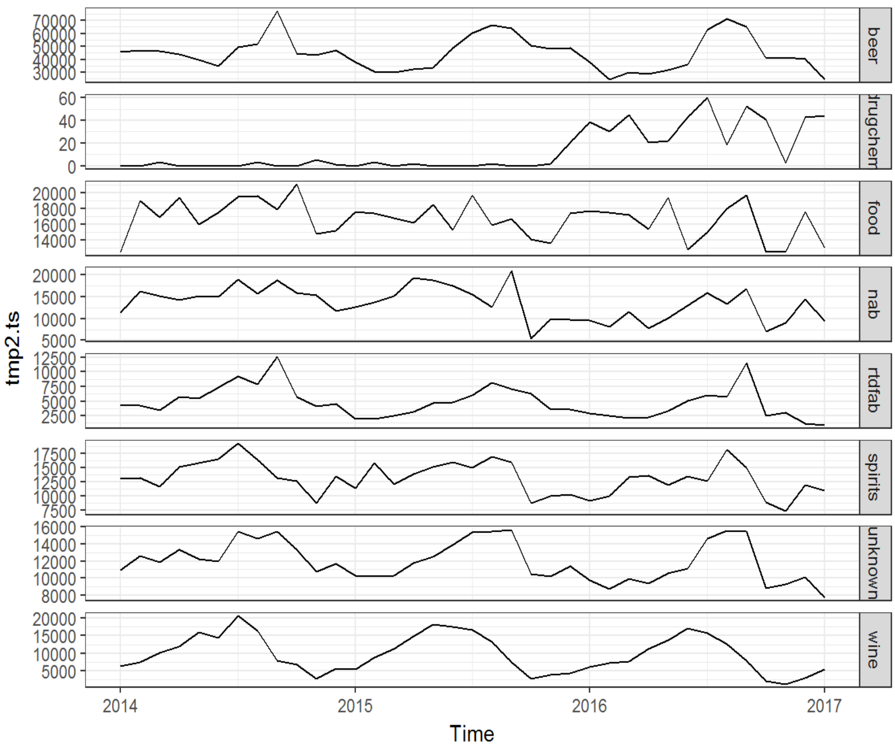
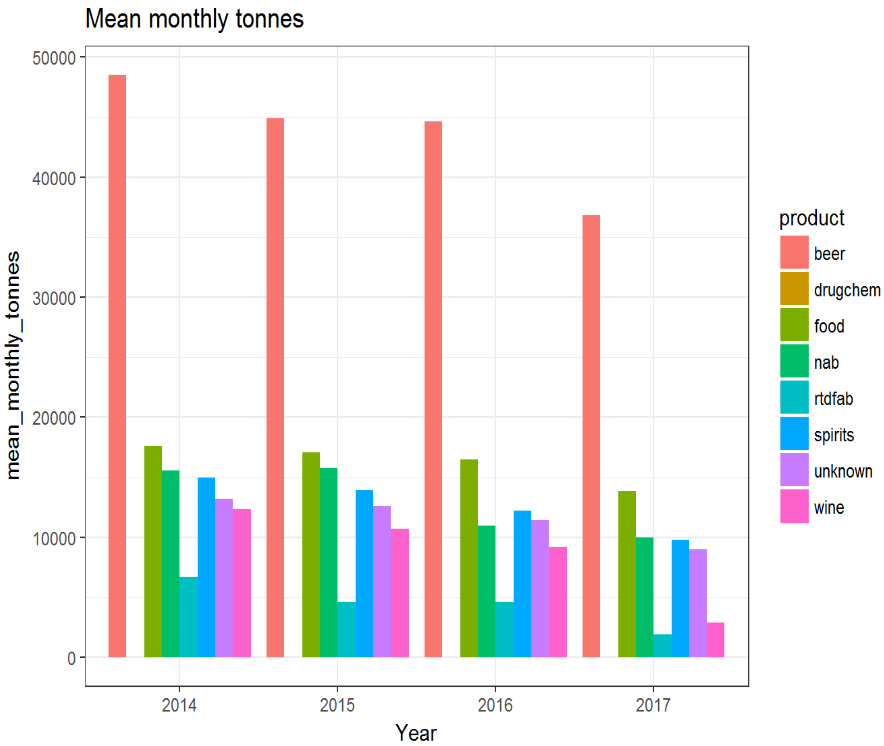
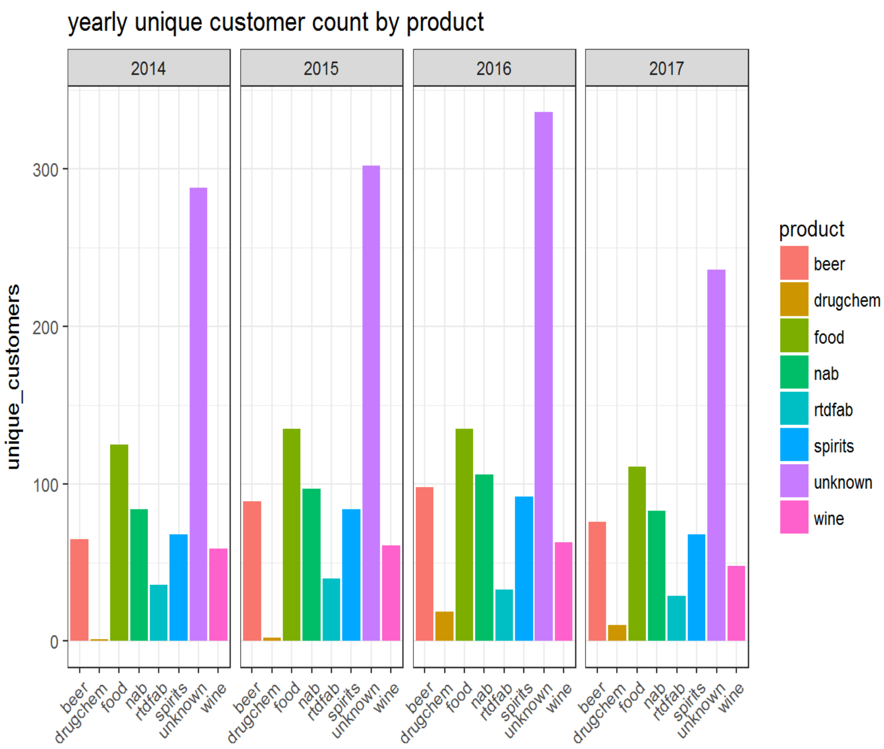


SE Belize Time Series

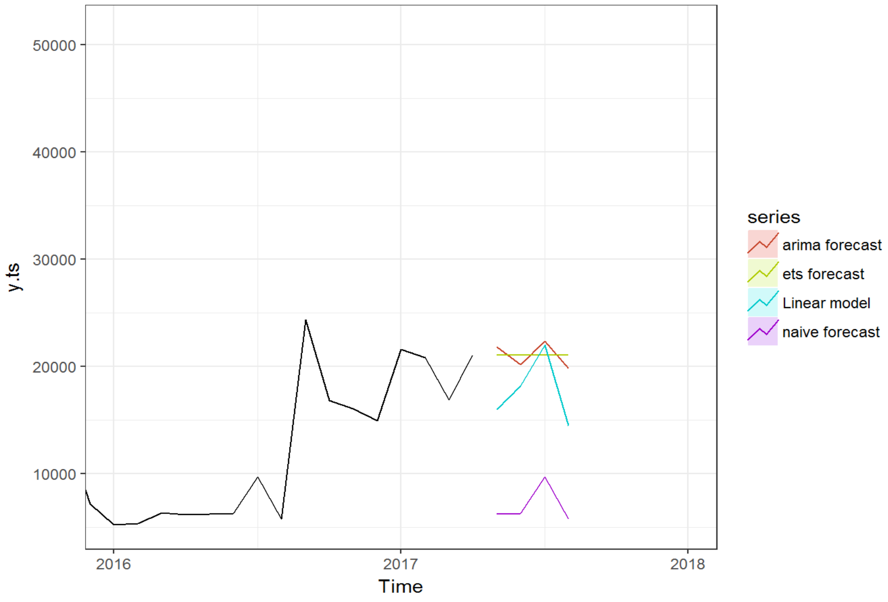


SE Belize annual mean tons shipped

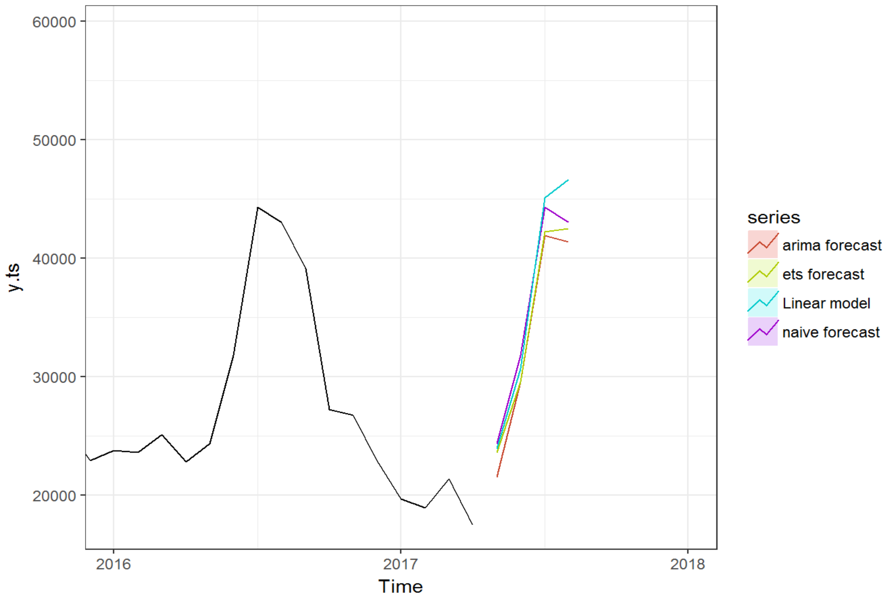


SE Belize unique customer count

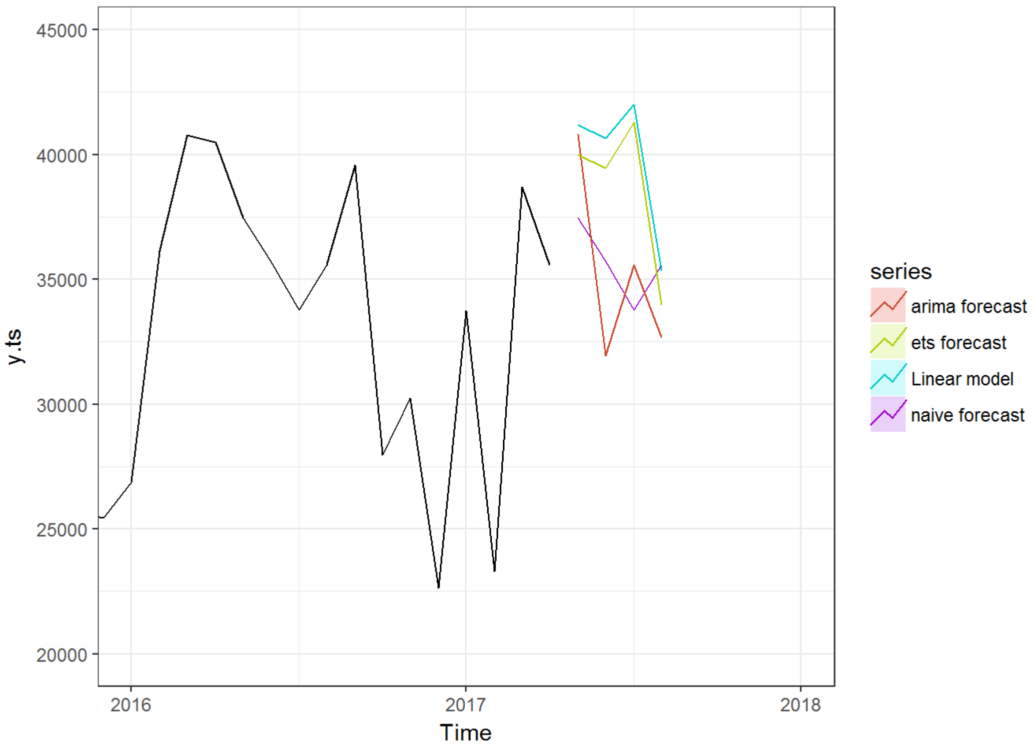
6.2 Forecasts for India



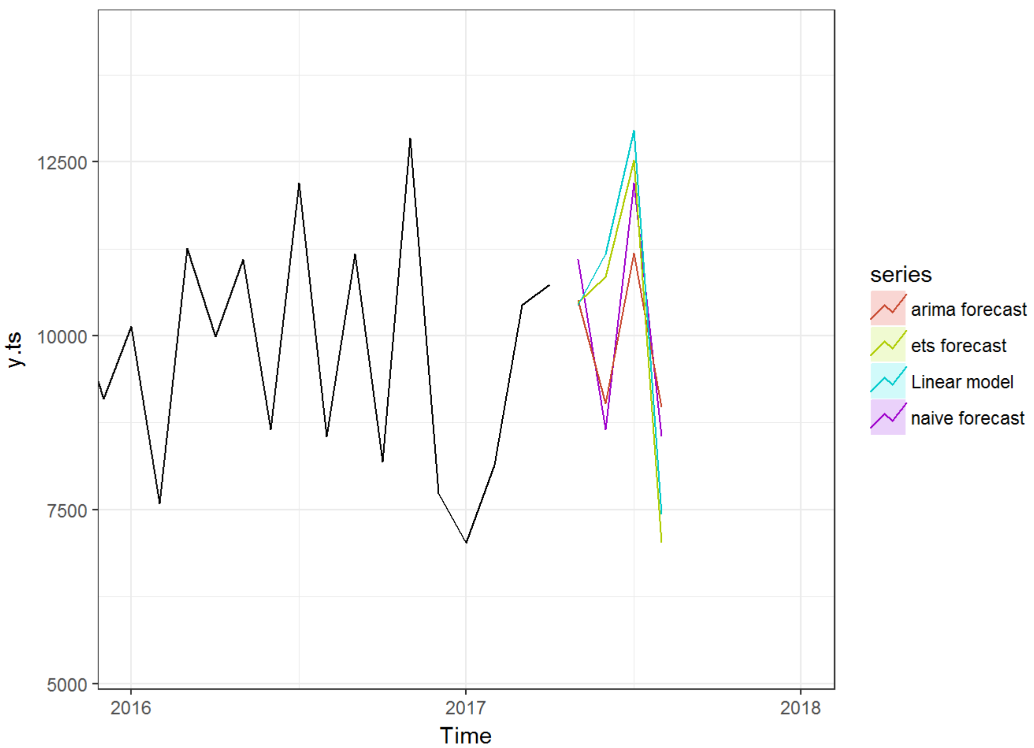
Forecasts for Beer



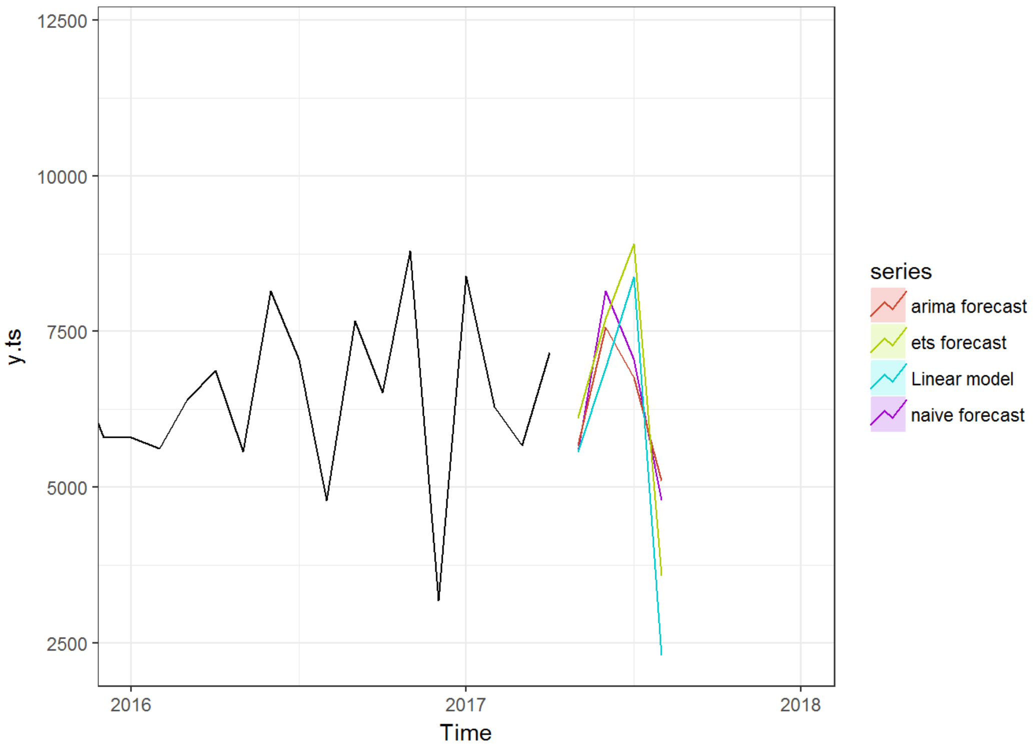
Forecasts for Food



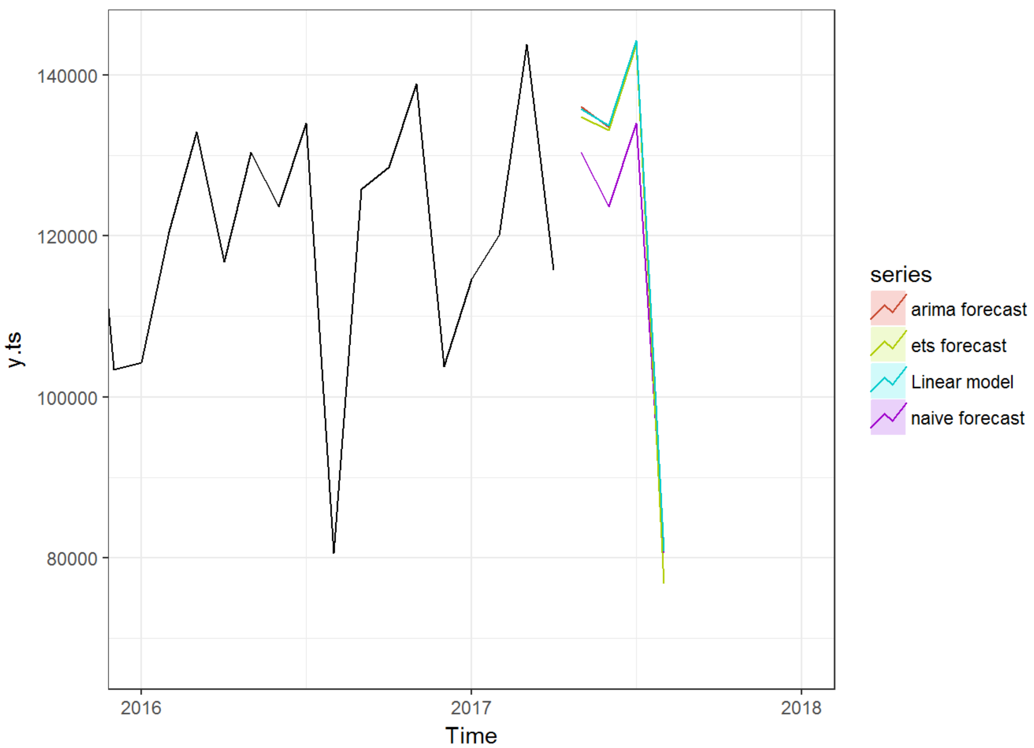
Forecasts for NAB



Forecasts for RTDFAB

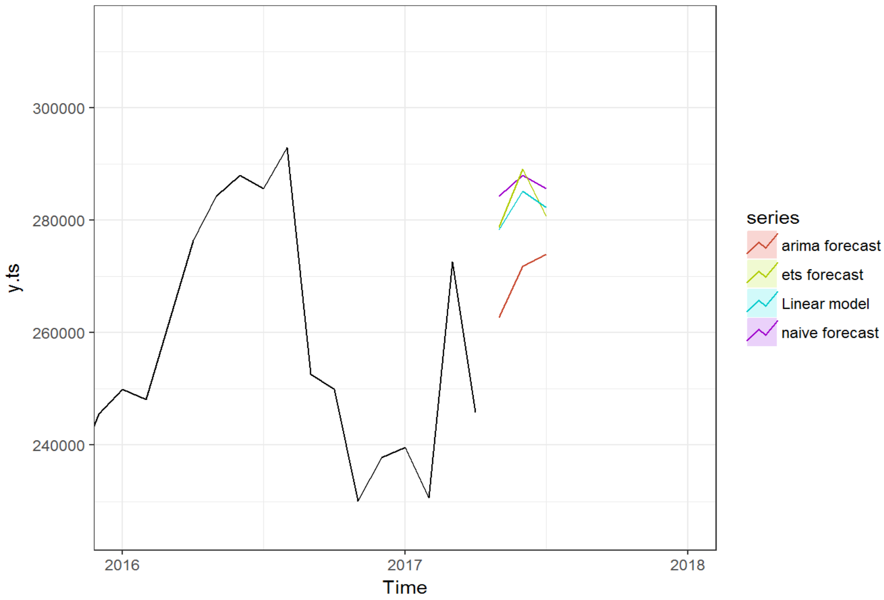


Forecasts for Spirits

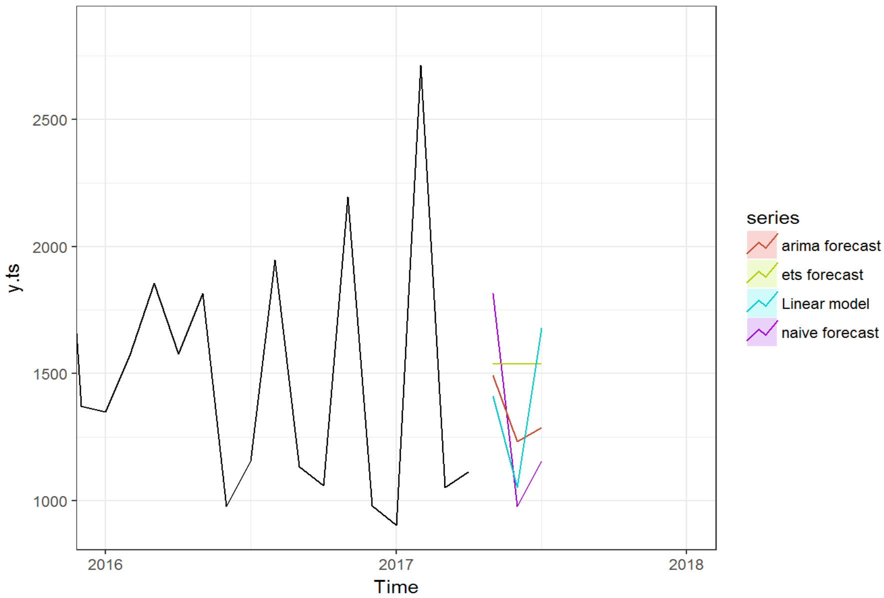


Forecasts for Wine

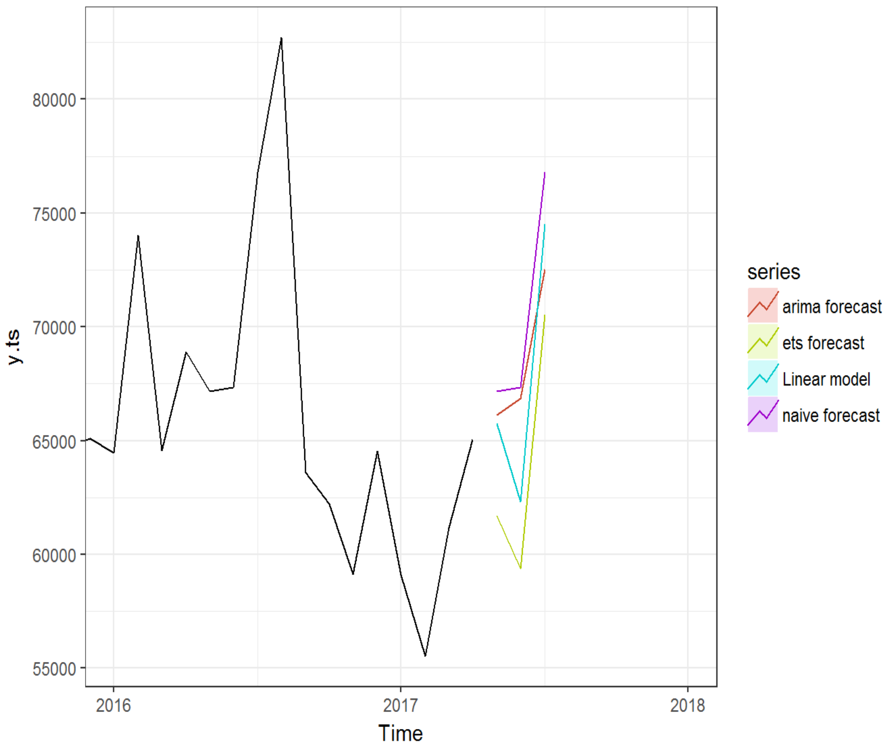
6.3 Forecasts for Uganda



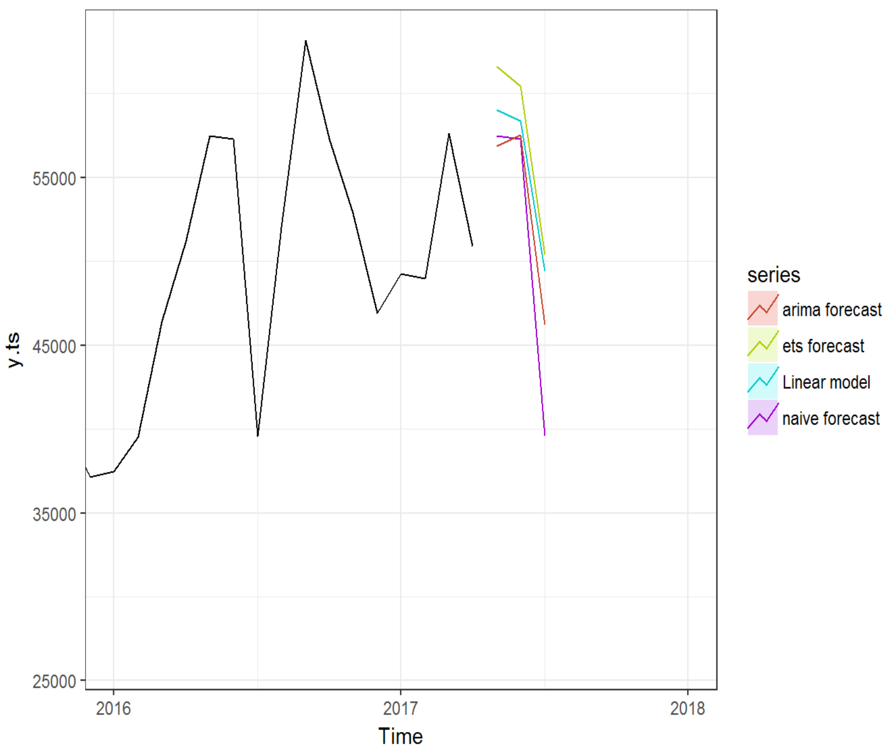
Forecasts for Beer



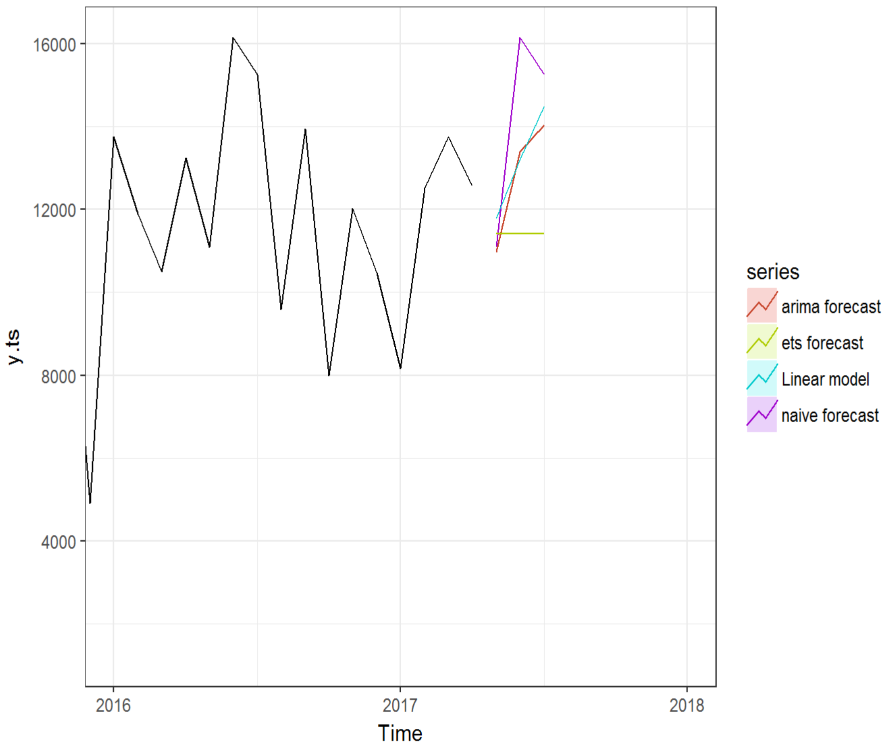
Forecasts for Drugs and Chemicals



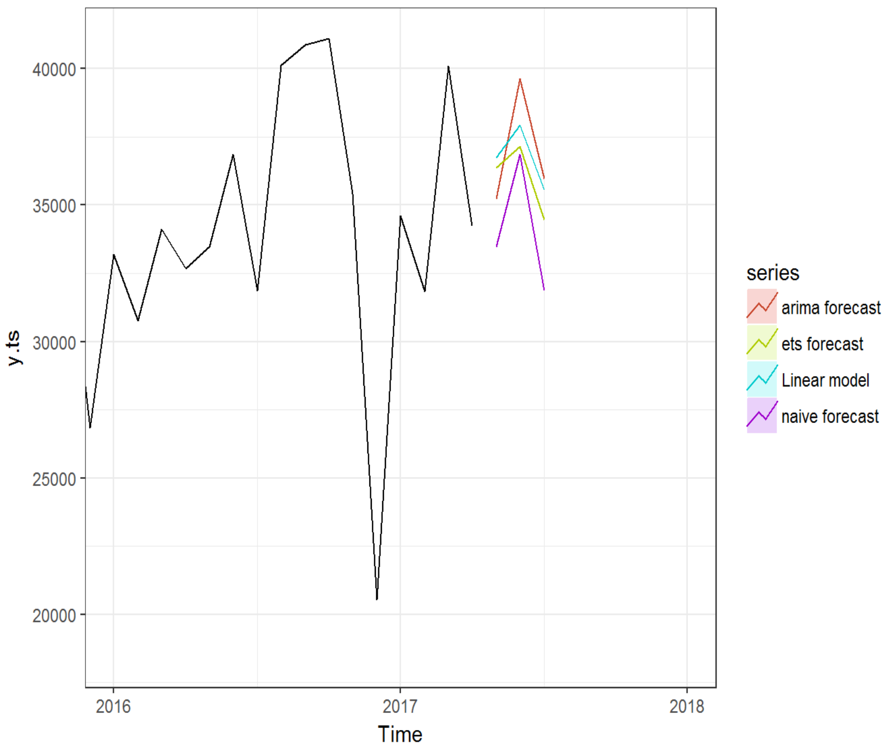
Forecasts for Food



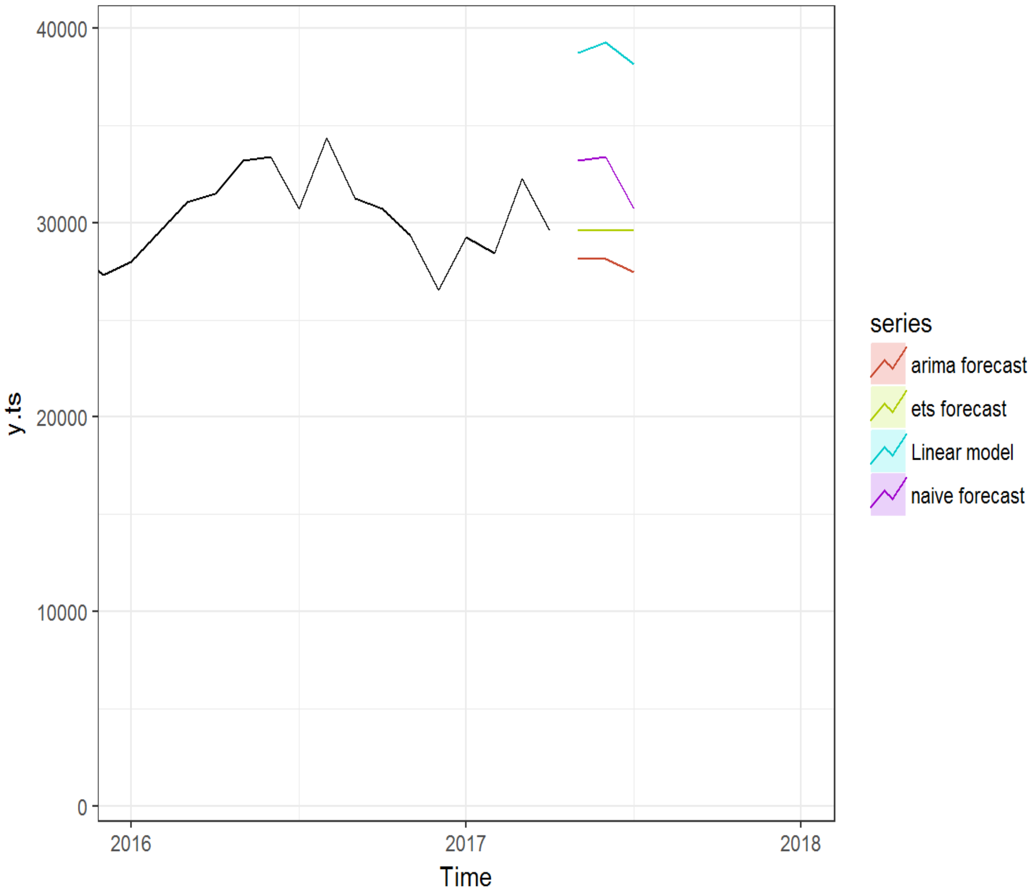
Forecasts for NAB



Forecasts for RTDFAB

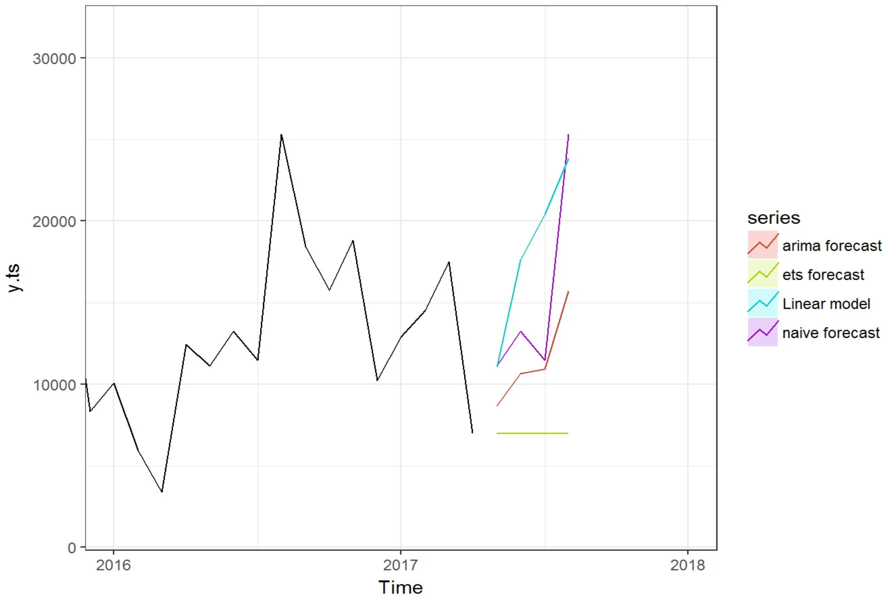


Forecasts for Spirits

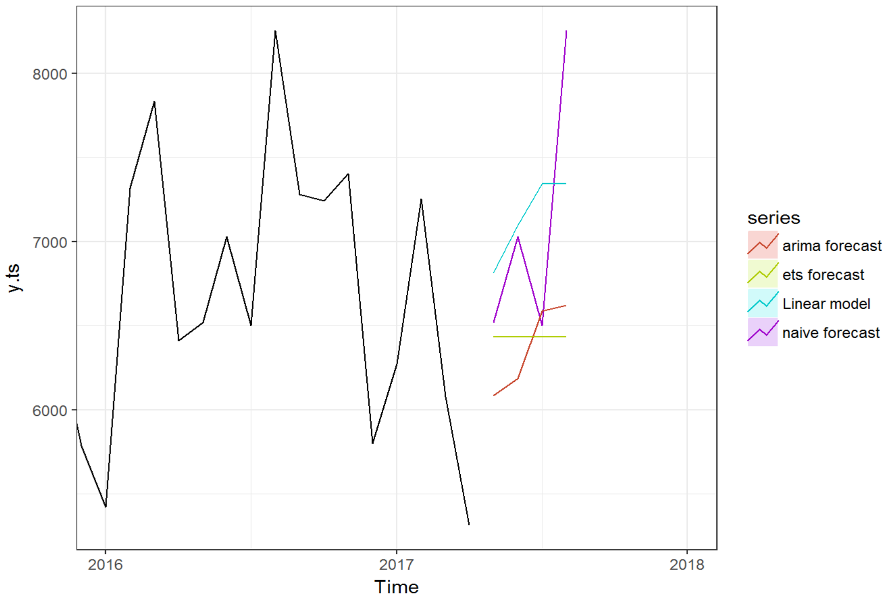


Forecasts for Unknown

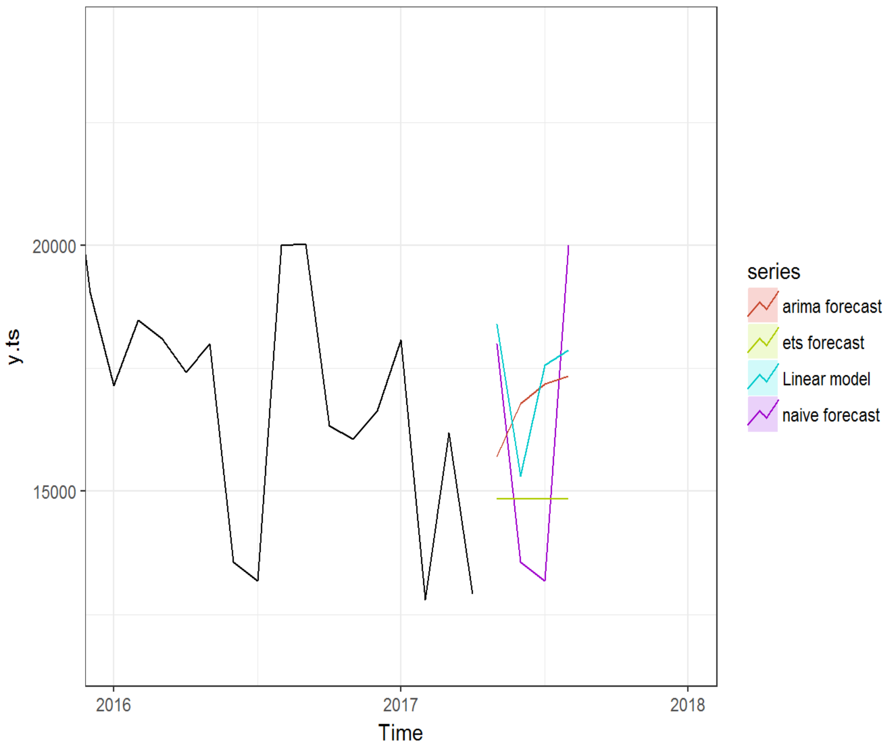
6.4 Forecasts for Congo



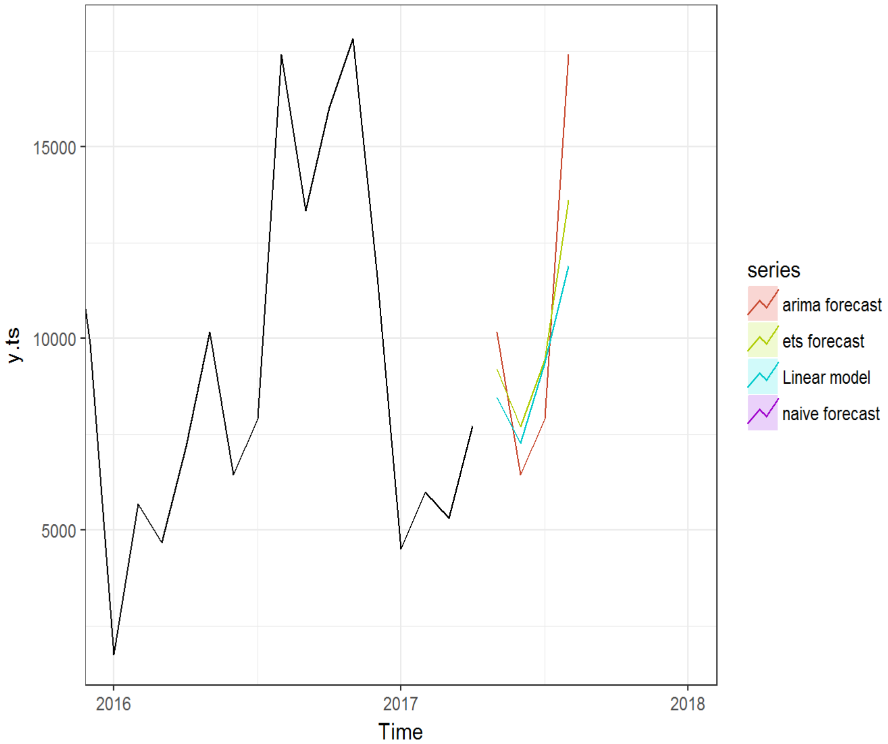
Forecasts for Beer



Forecasts for Food

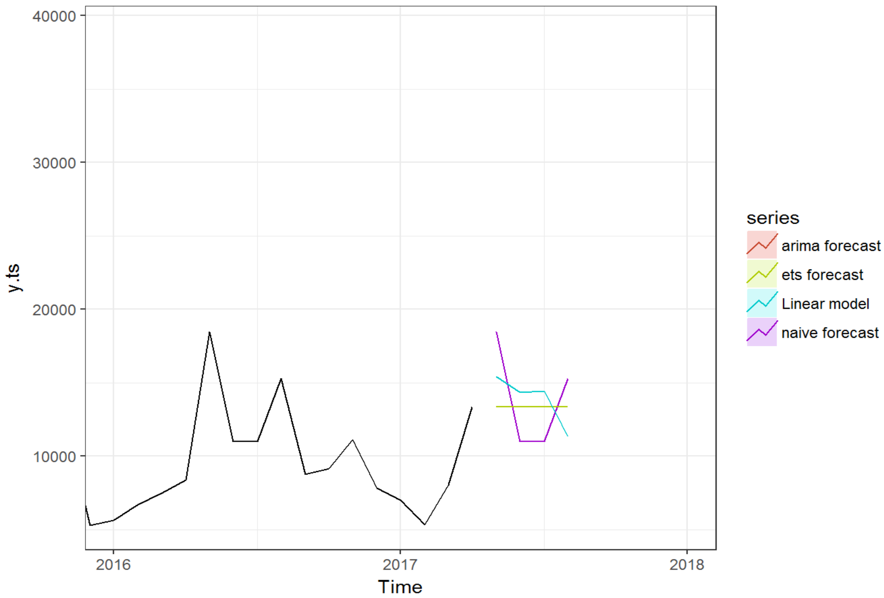


Forecasts for NAB

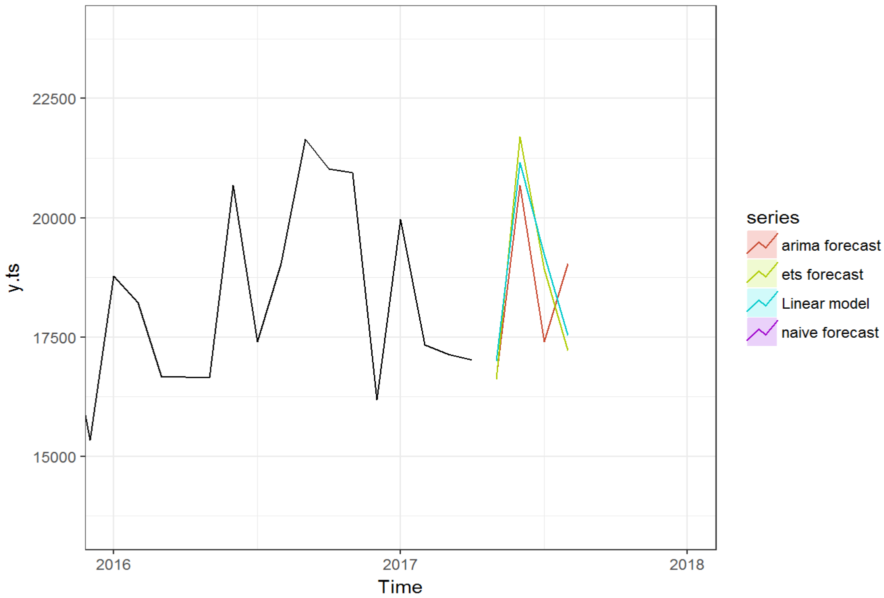


Forecasts for Spirits

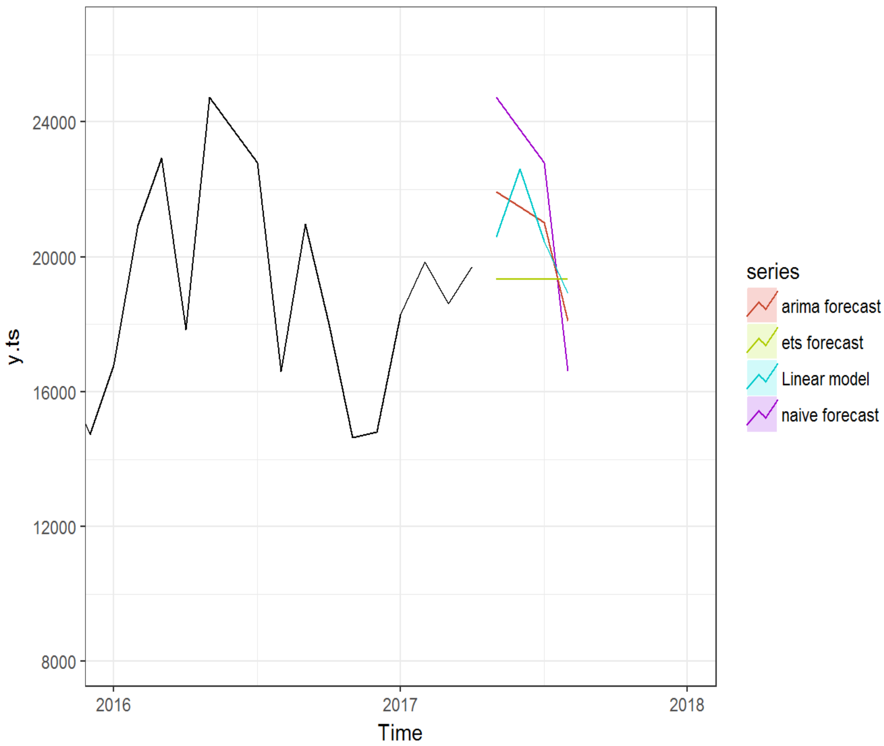
6.5 Forecasts for Finland



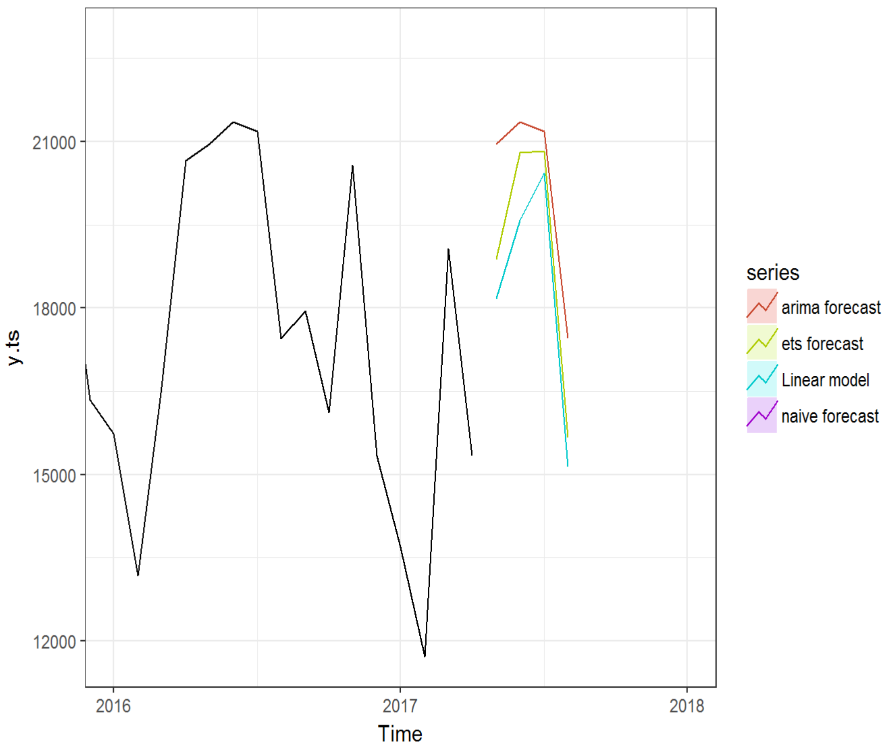
Forecasts for Beer



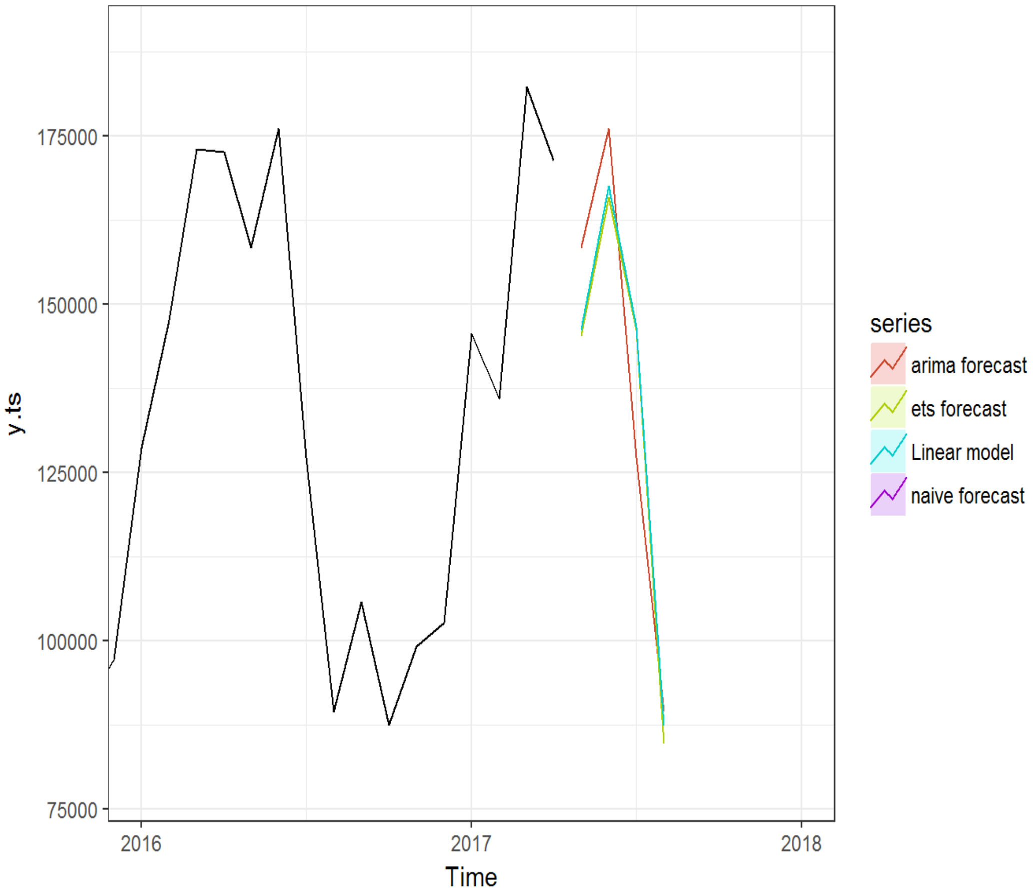
Forecasts for Food



Forecasts for NAB

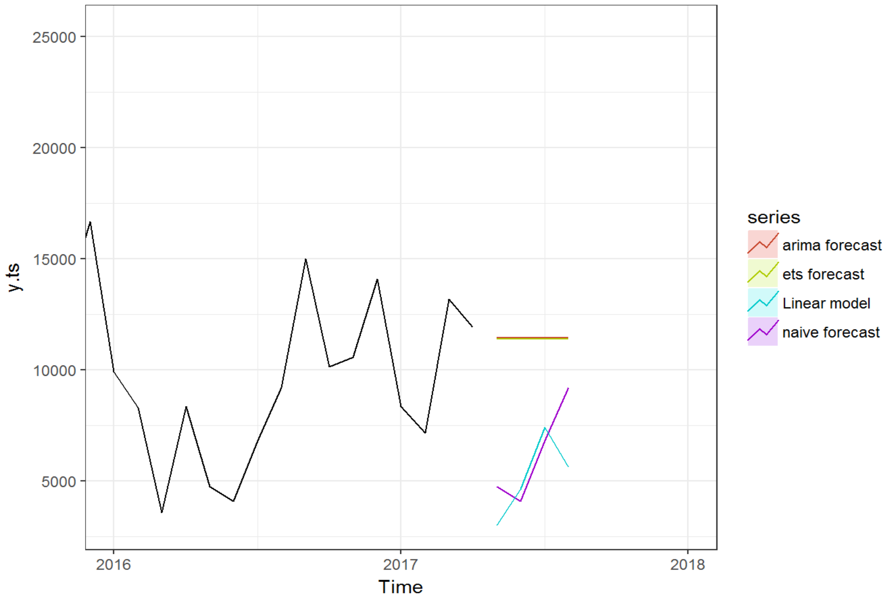


Forecasts for Spirits

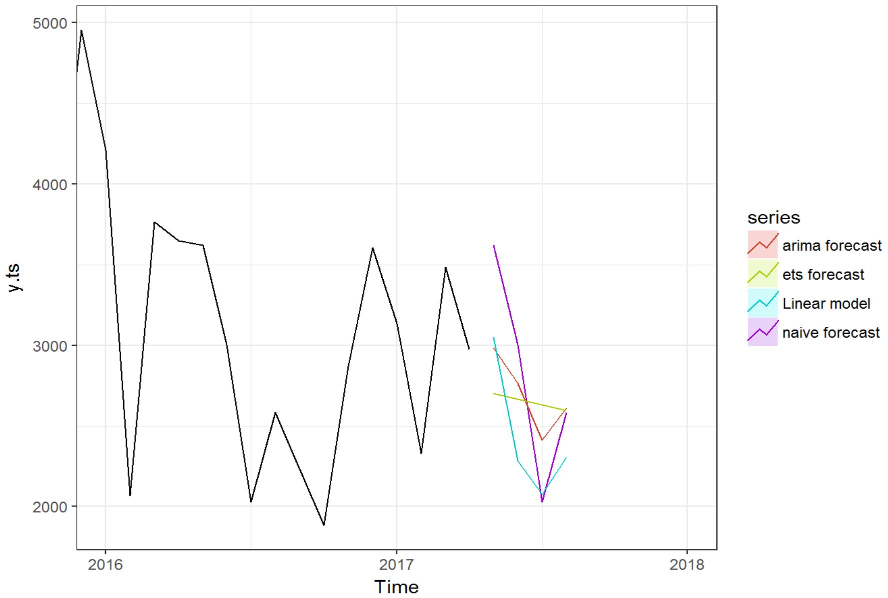


Forecasts for Wine

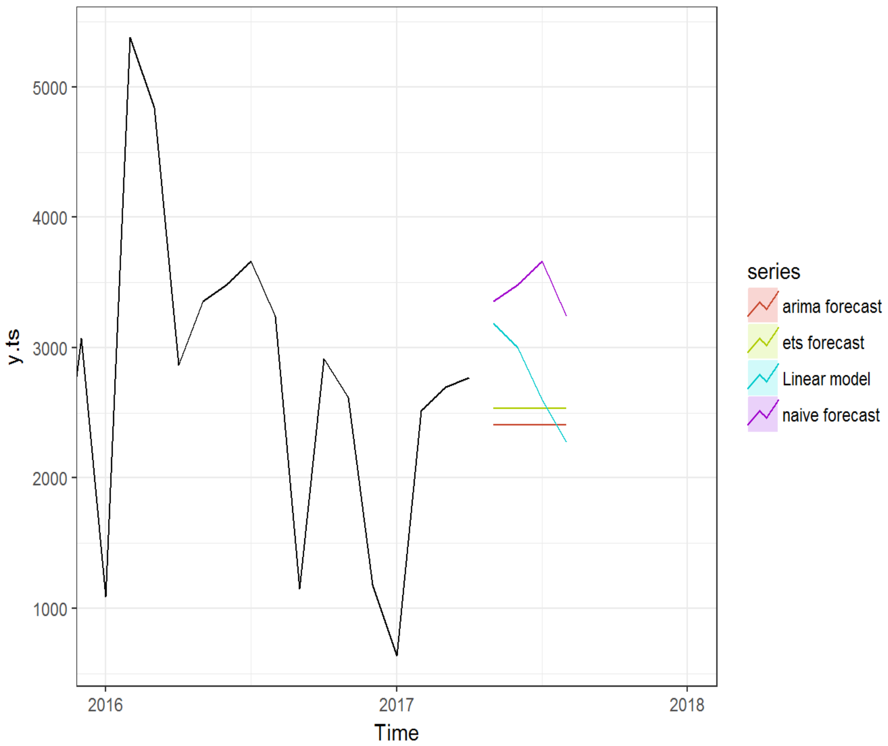
6.6 Forecasts for North East Belize



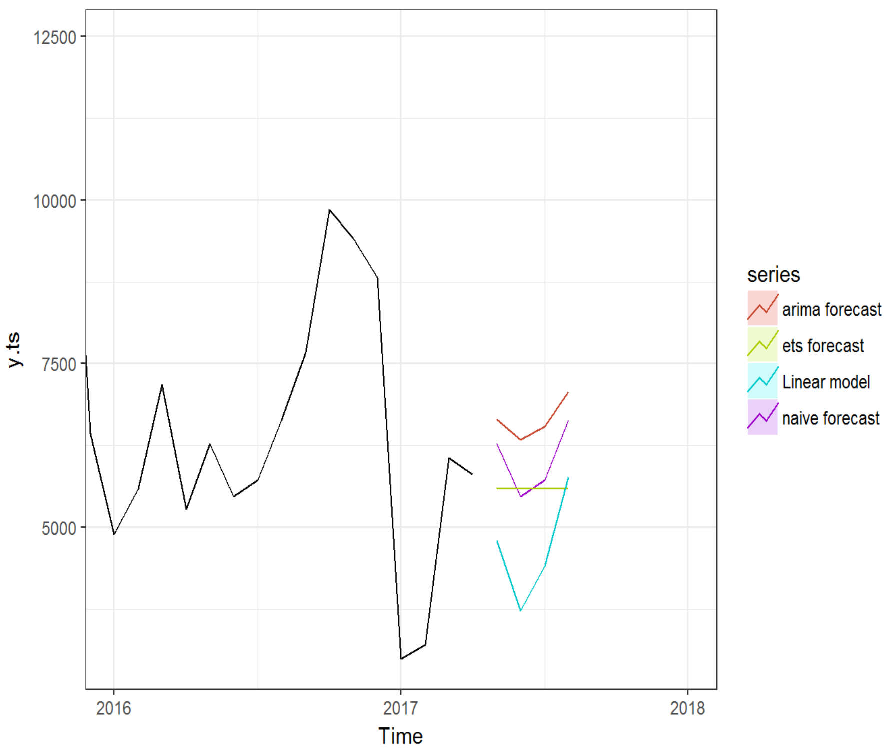
Forecasts for Beer



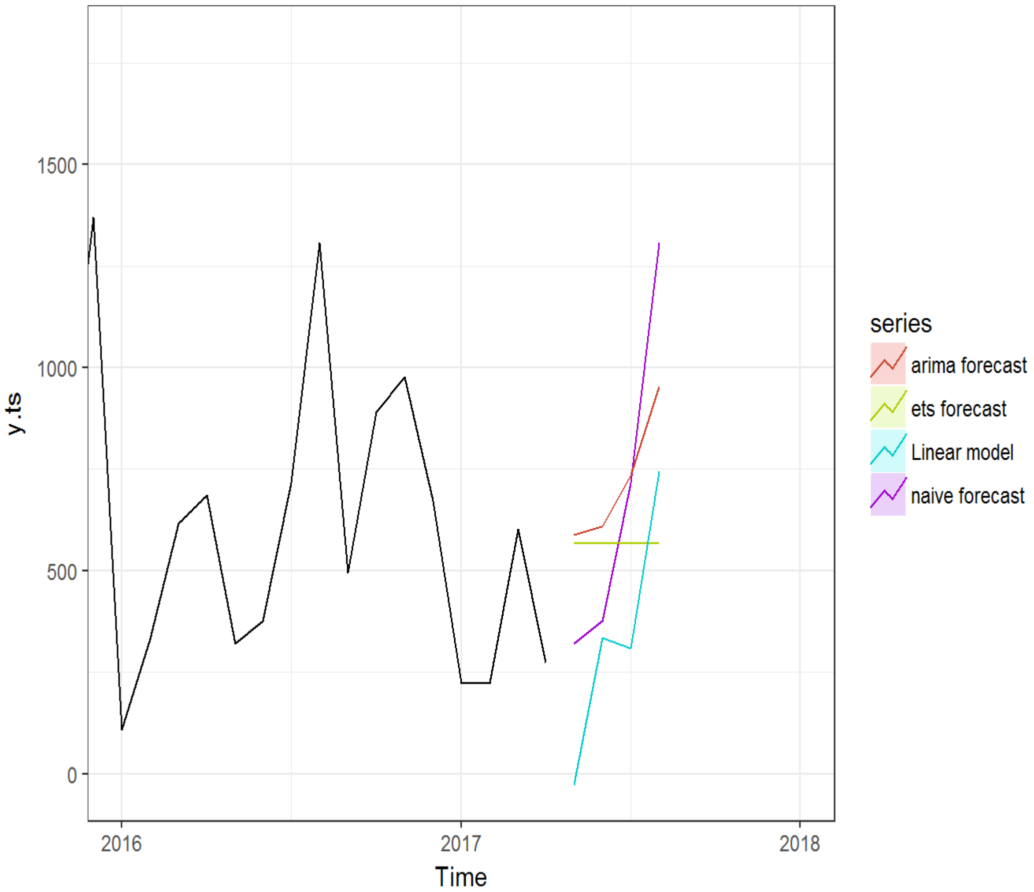
Forecasts for Food



Forecasts for NAB

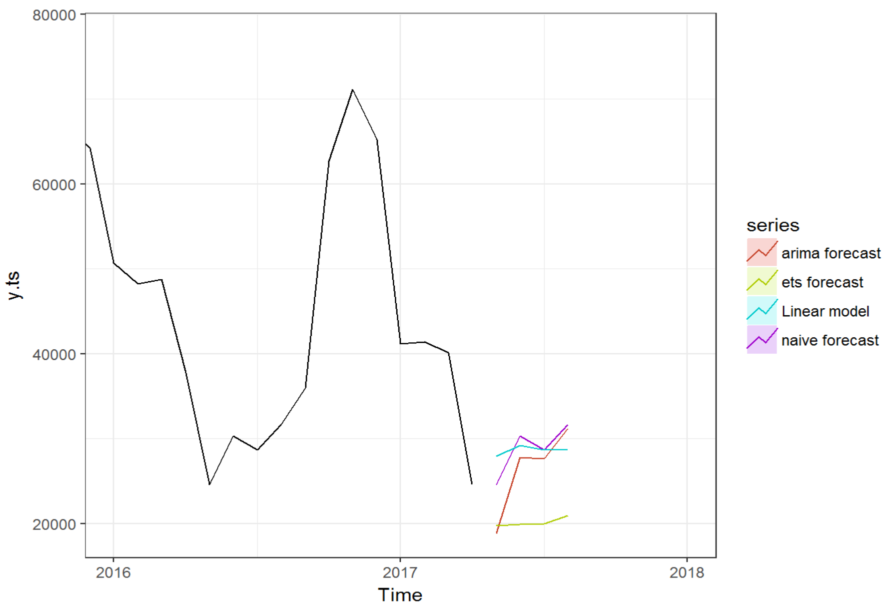


Forecasts for Spirits

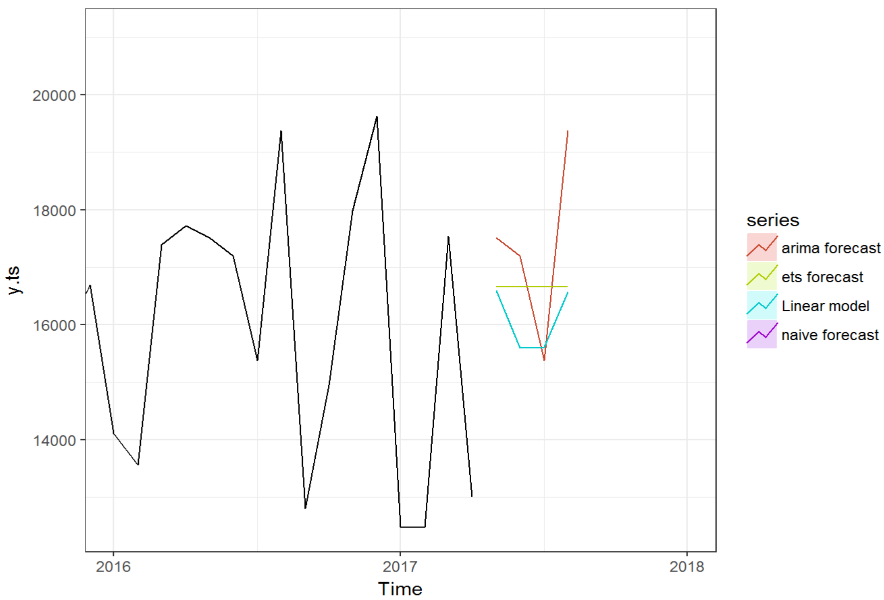


Forecasts for Wine

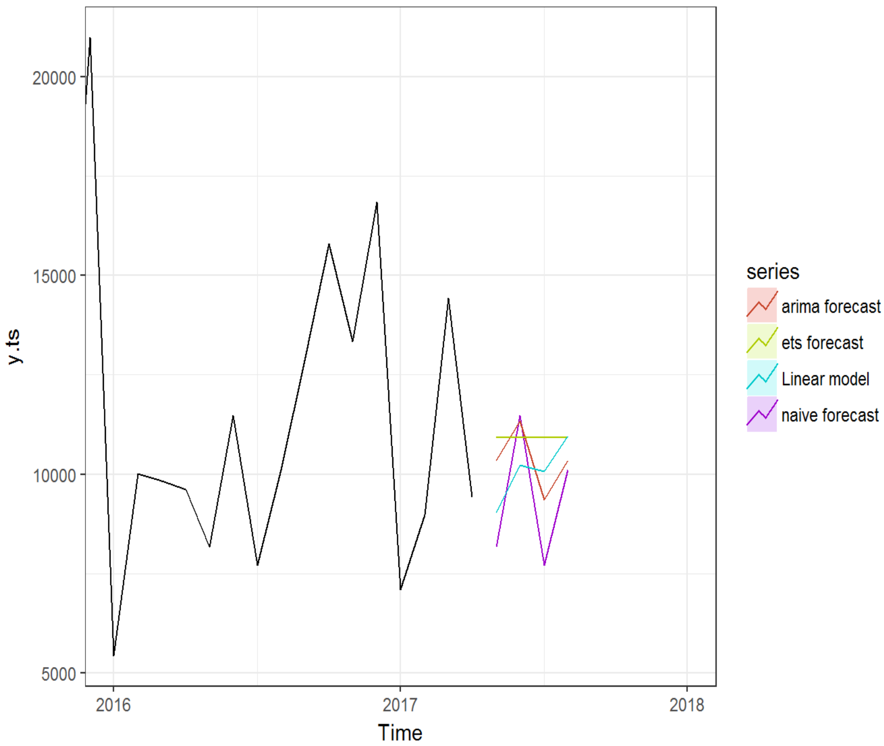
6.7 Forecasts for South East Belize



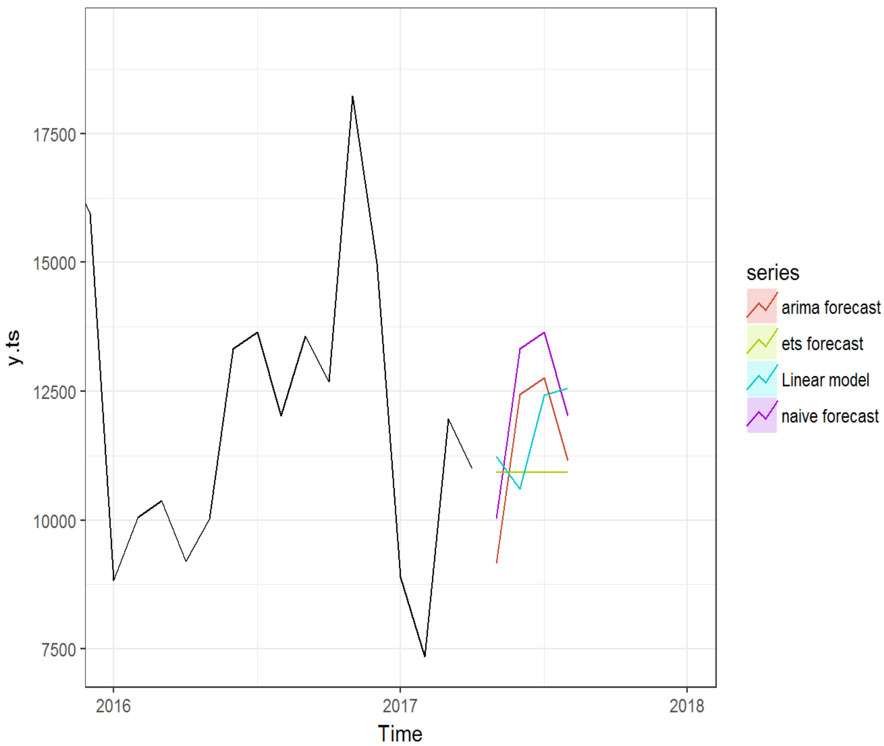
Forecasts for Beer



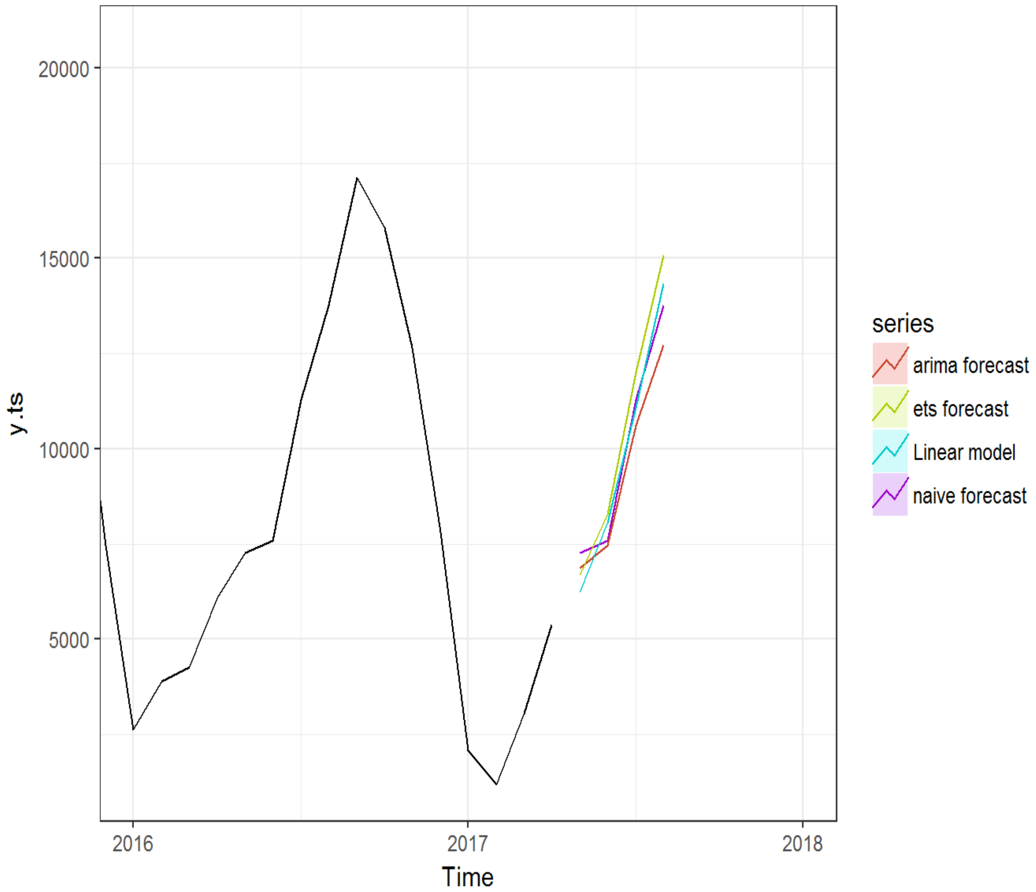
Forecasts for Food



Forecasts for NAB

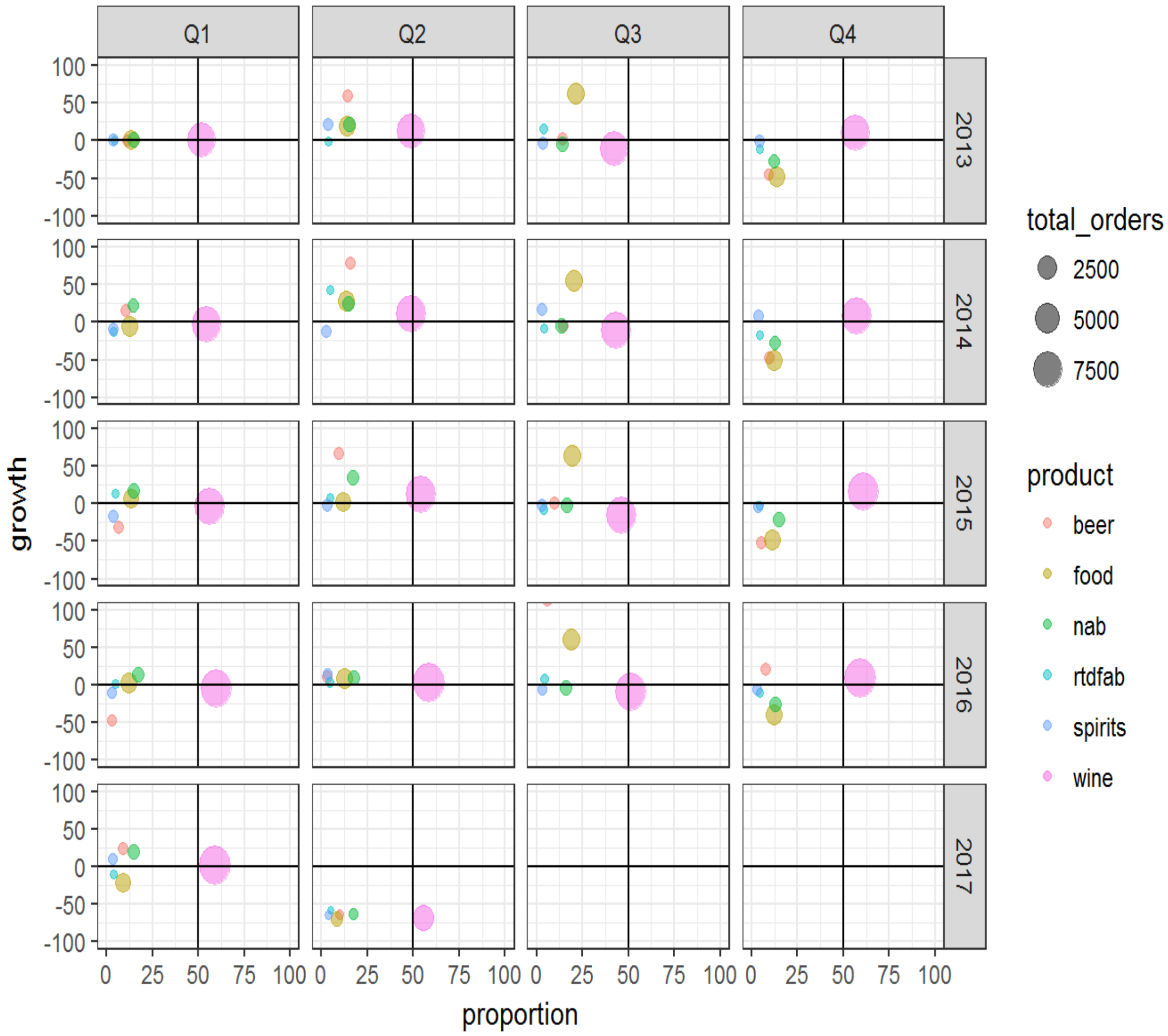


Forecasts for Spirits

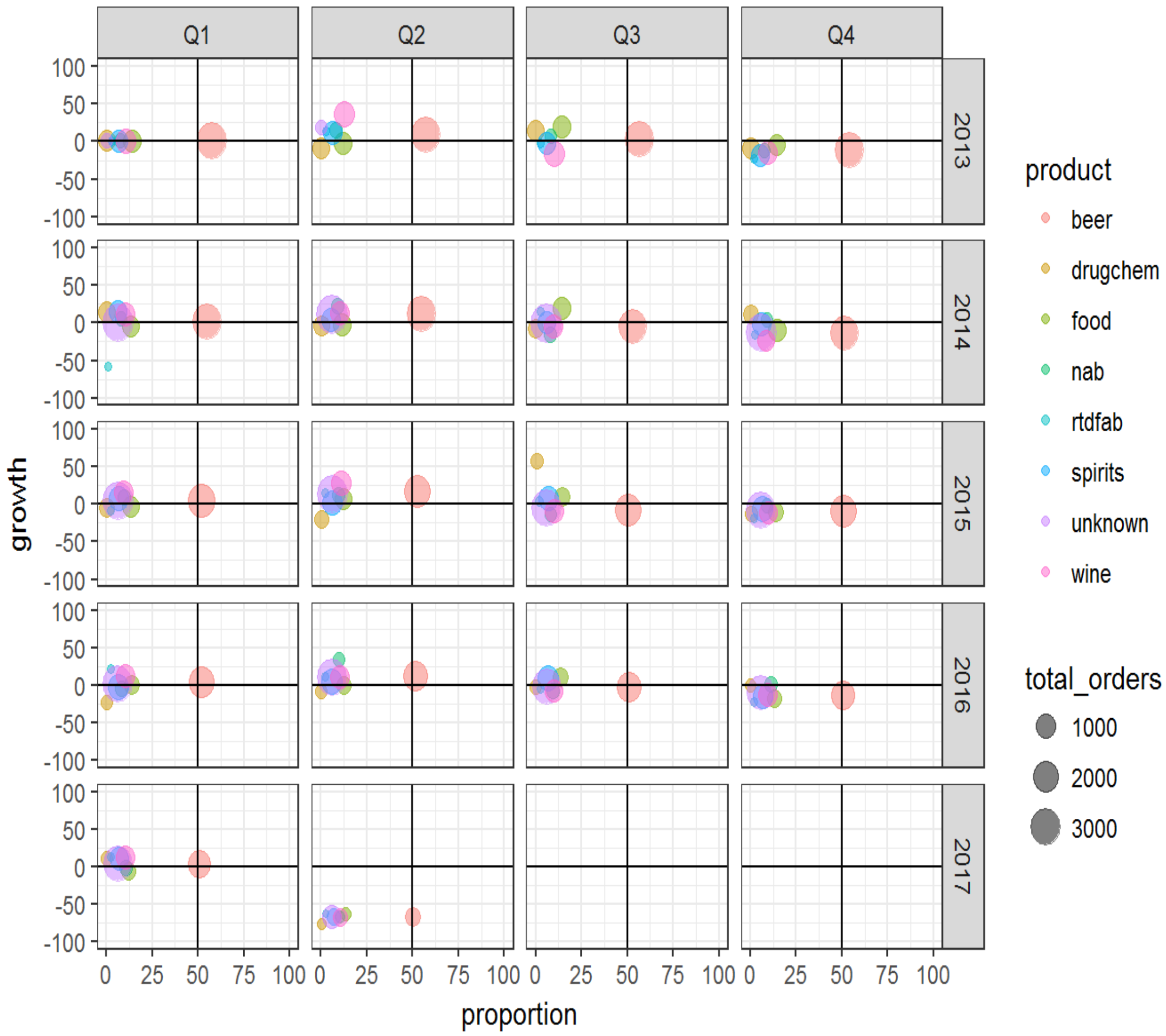


Forecasts for Wine

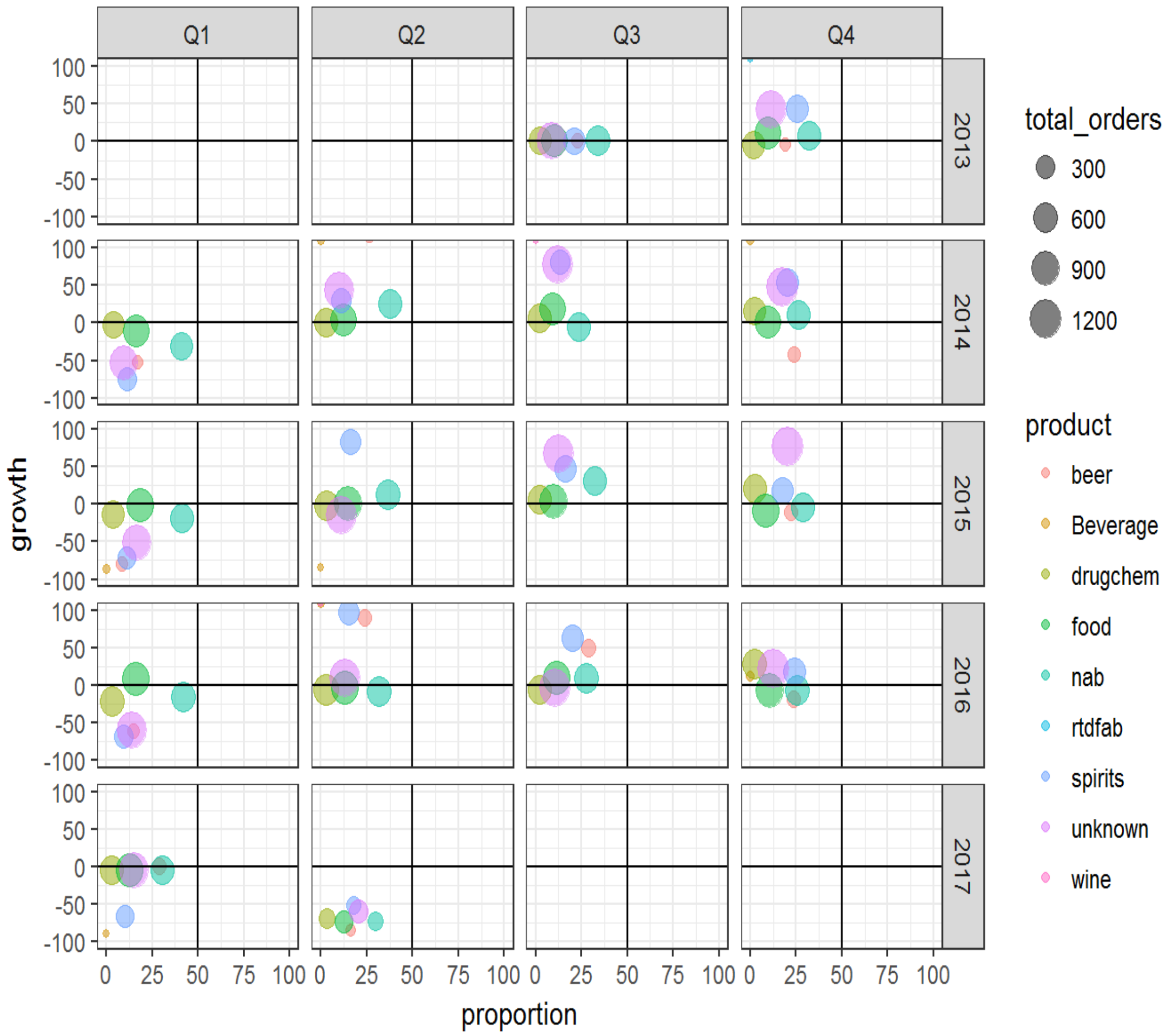
6.8 Product Segmentation



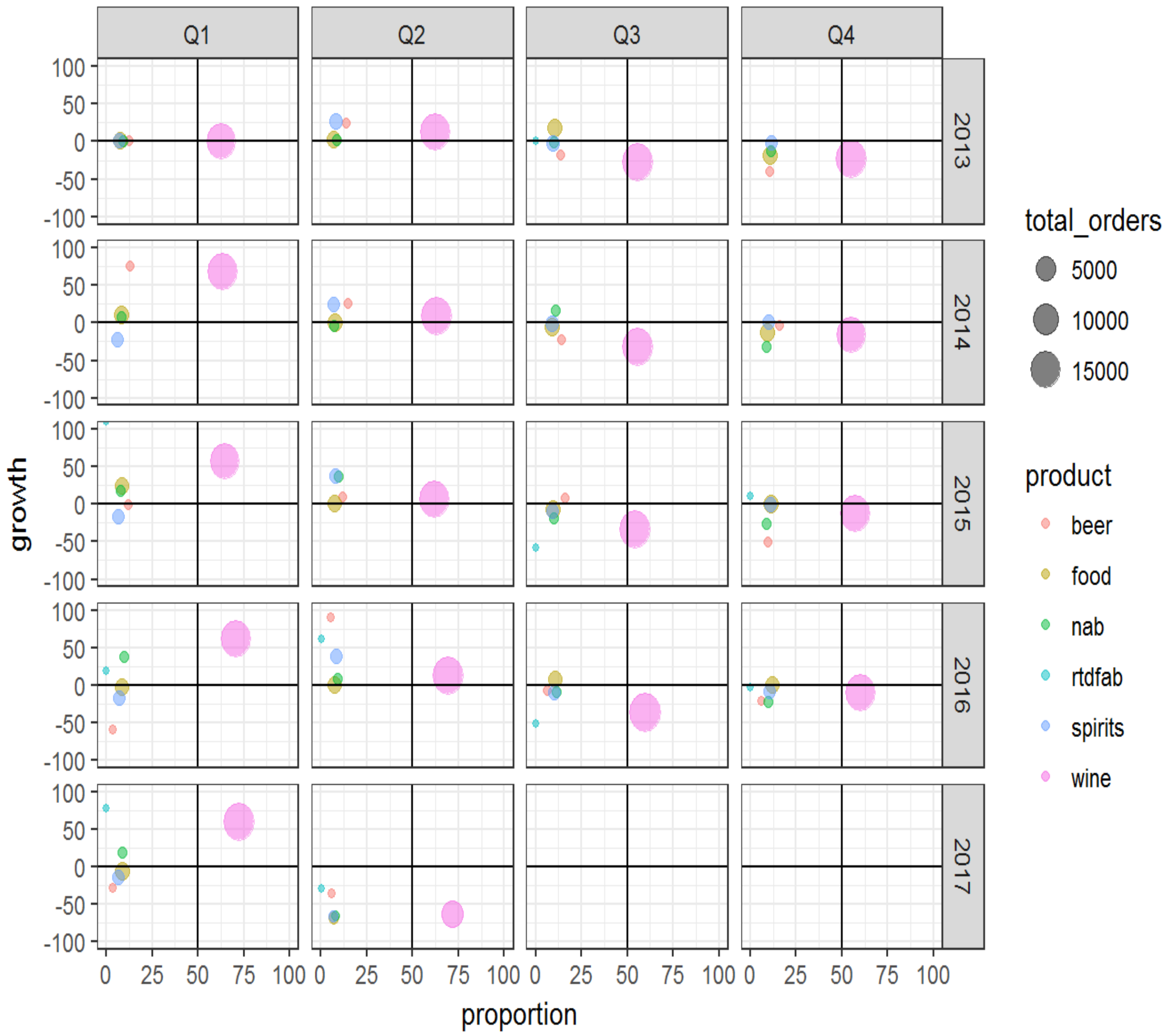
India Product Segmentation



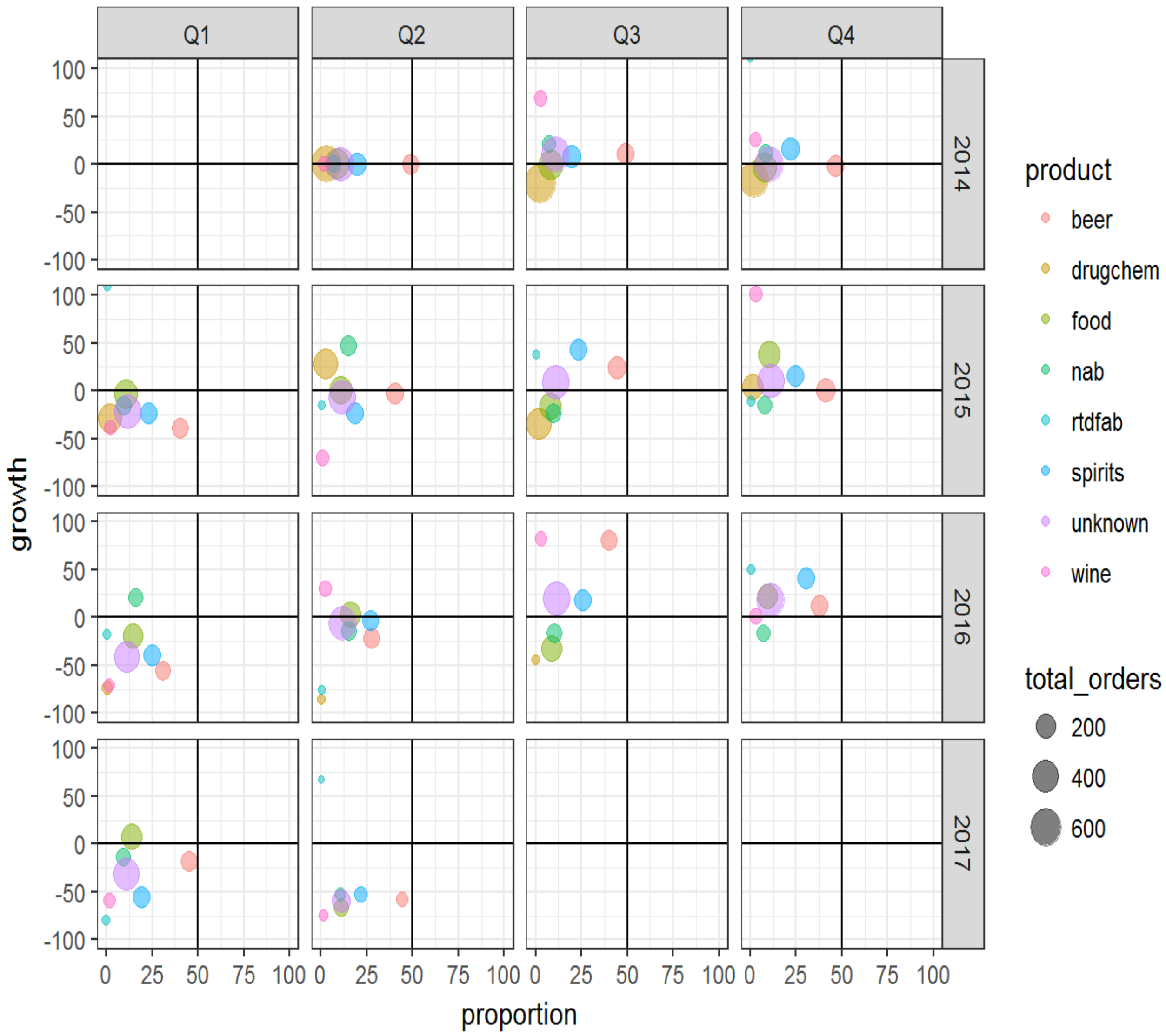
Uganda Product Segmentation



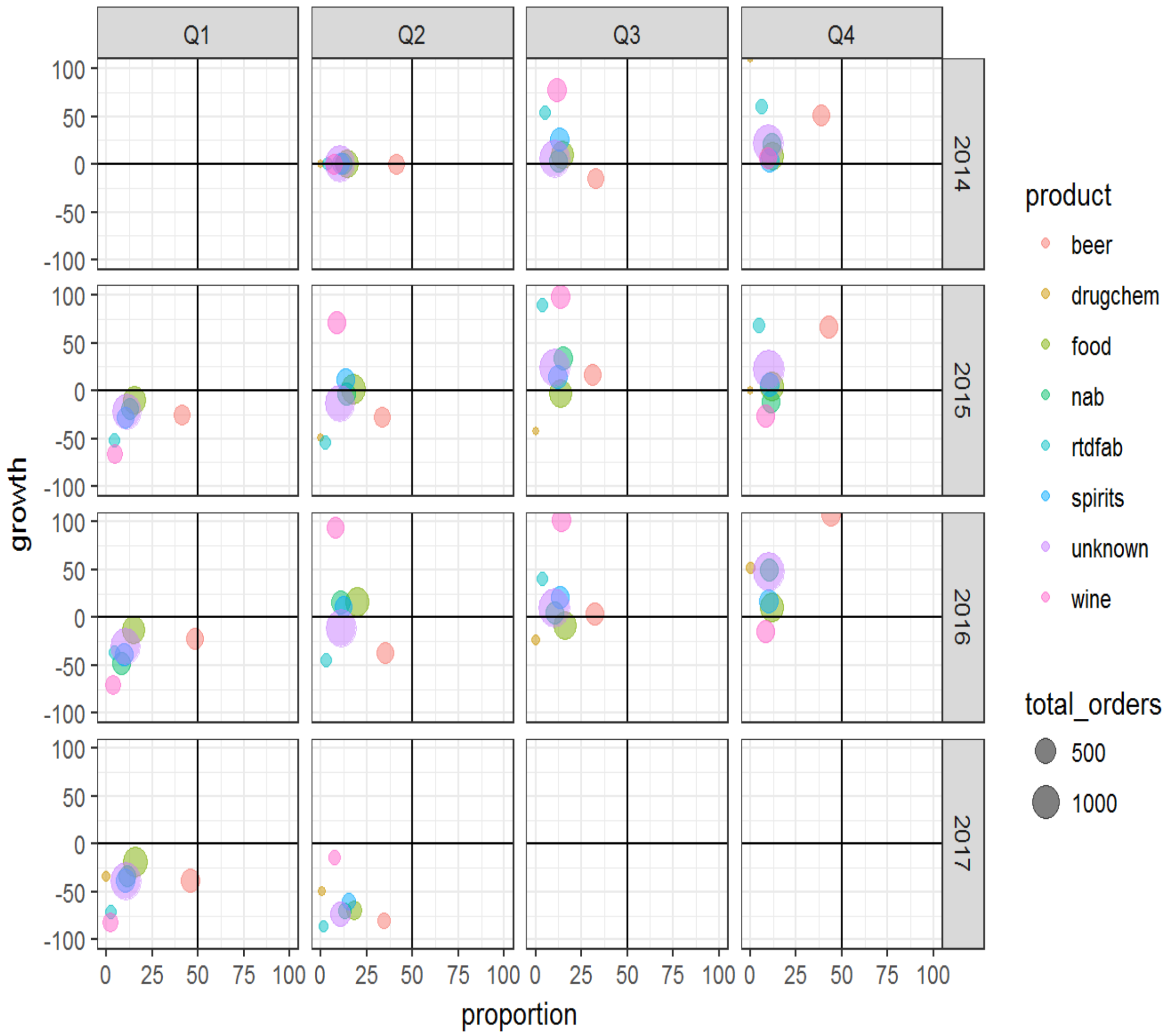
Congo Product Segmentation



Finland Product Segmentation

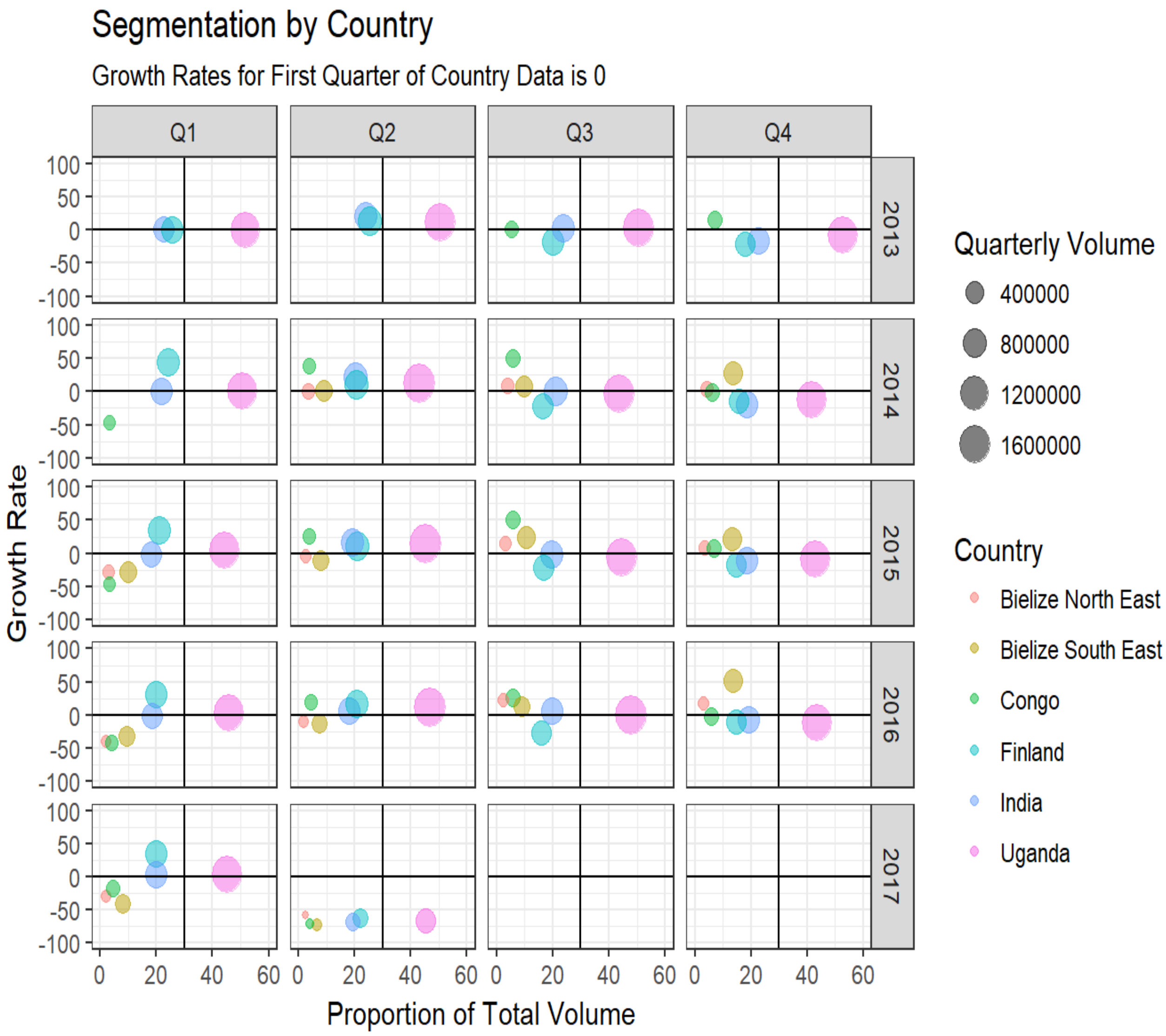


North East Belize Product Segmentation

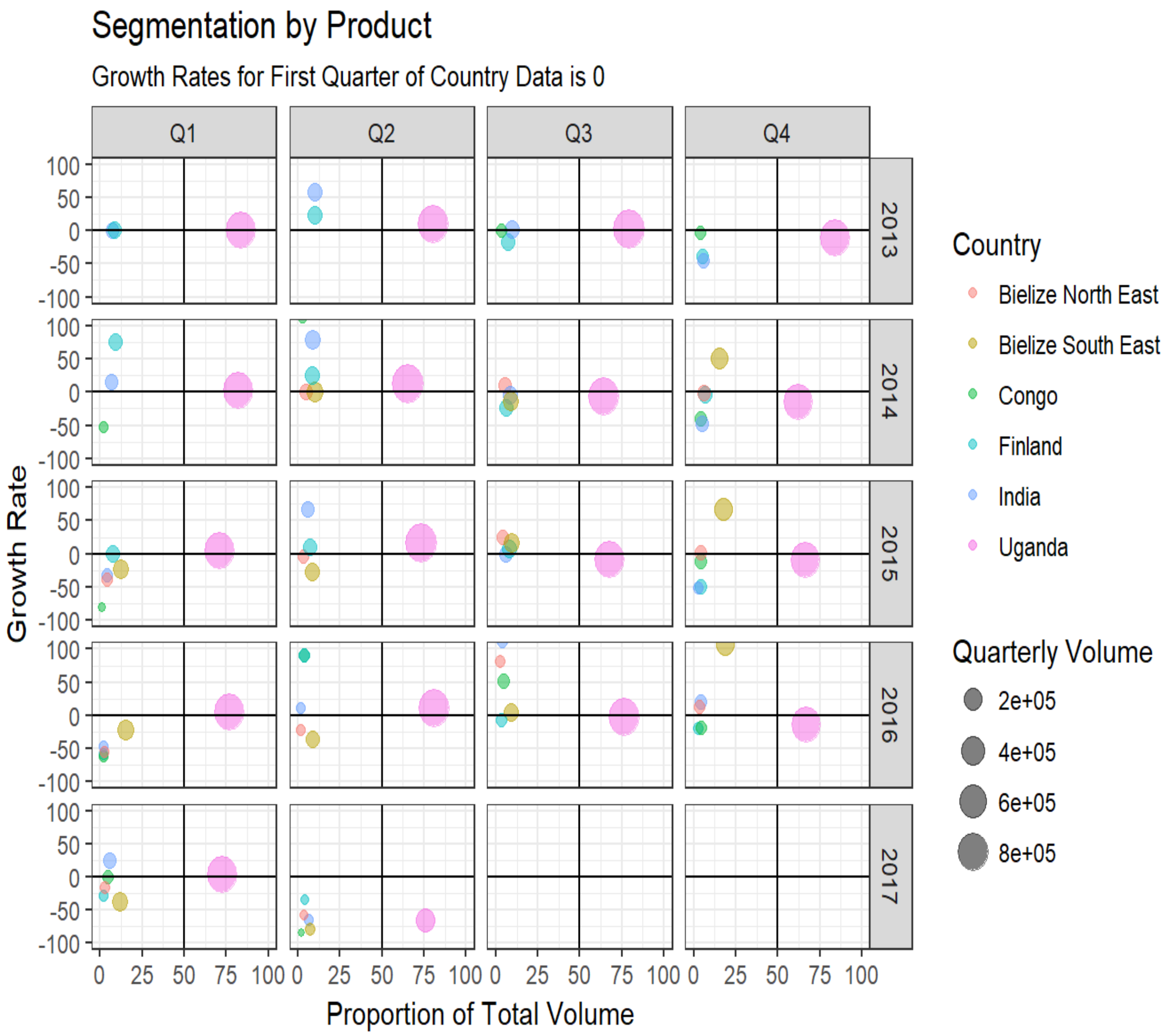


South East Belize Product Segmentation

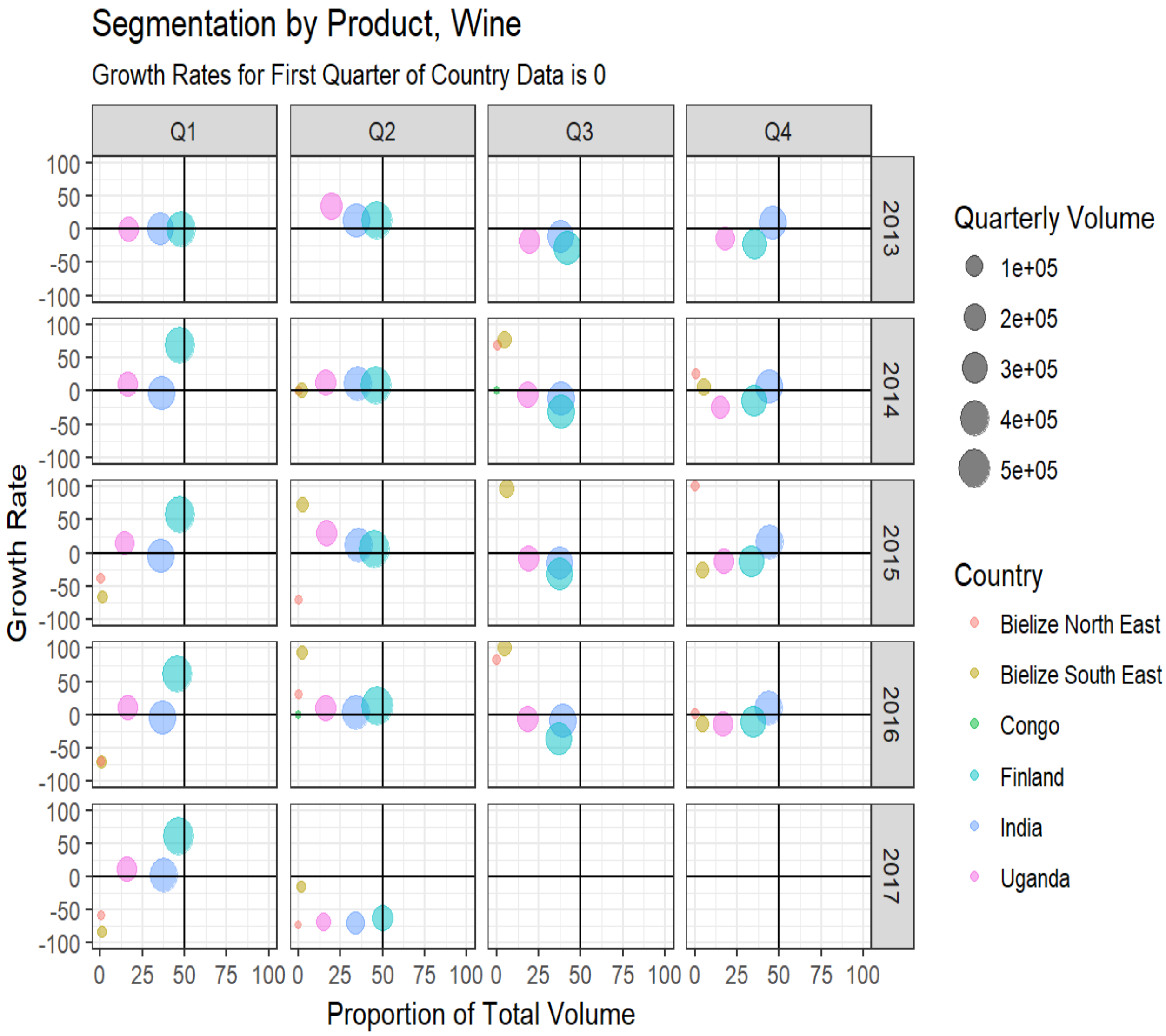
6.9 Country Segmentation



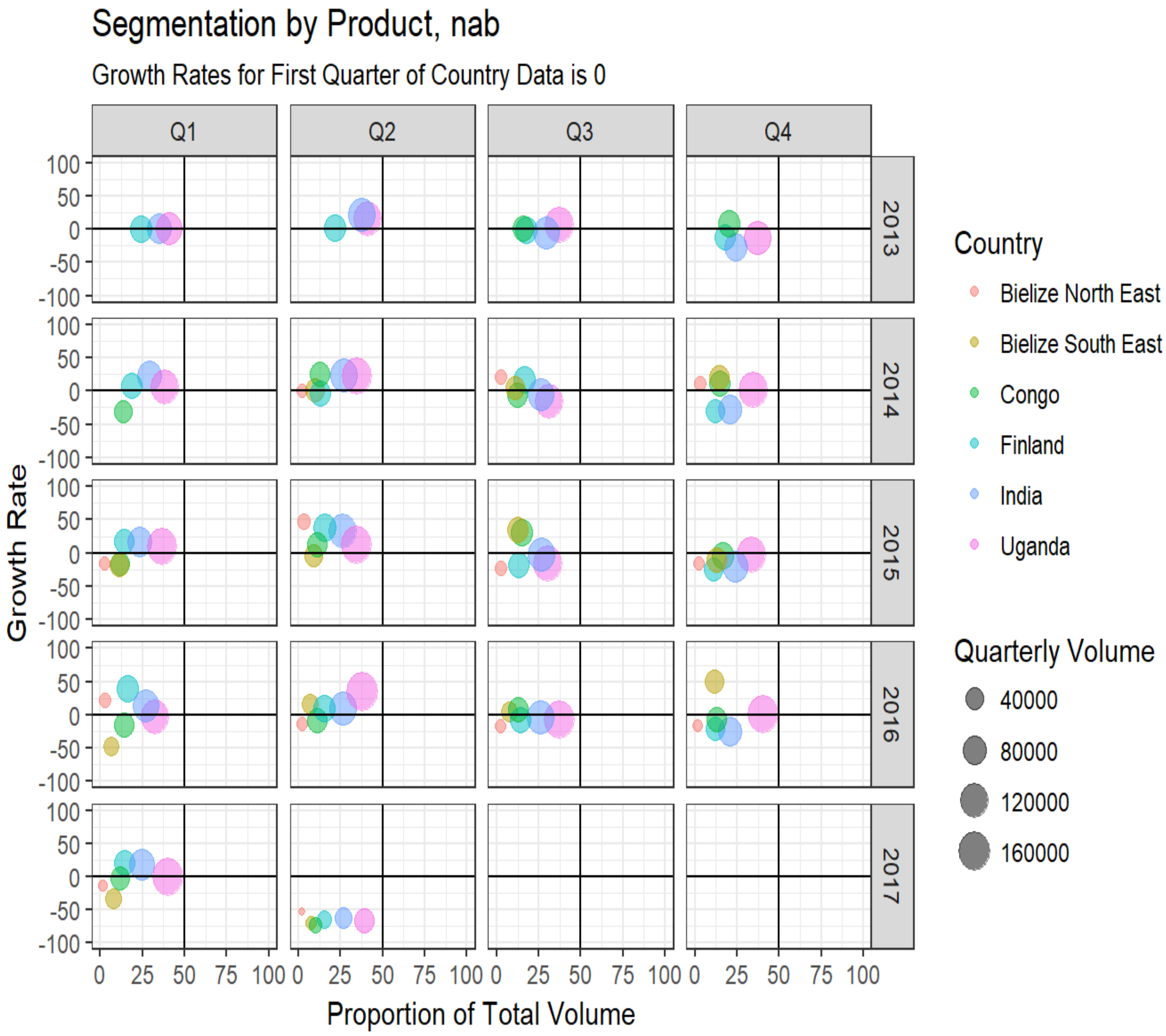
Overall Countries Segmentation



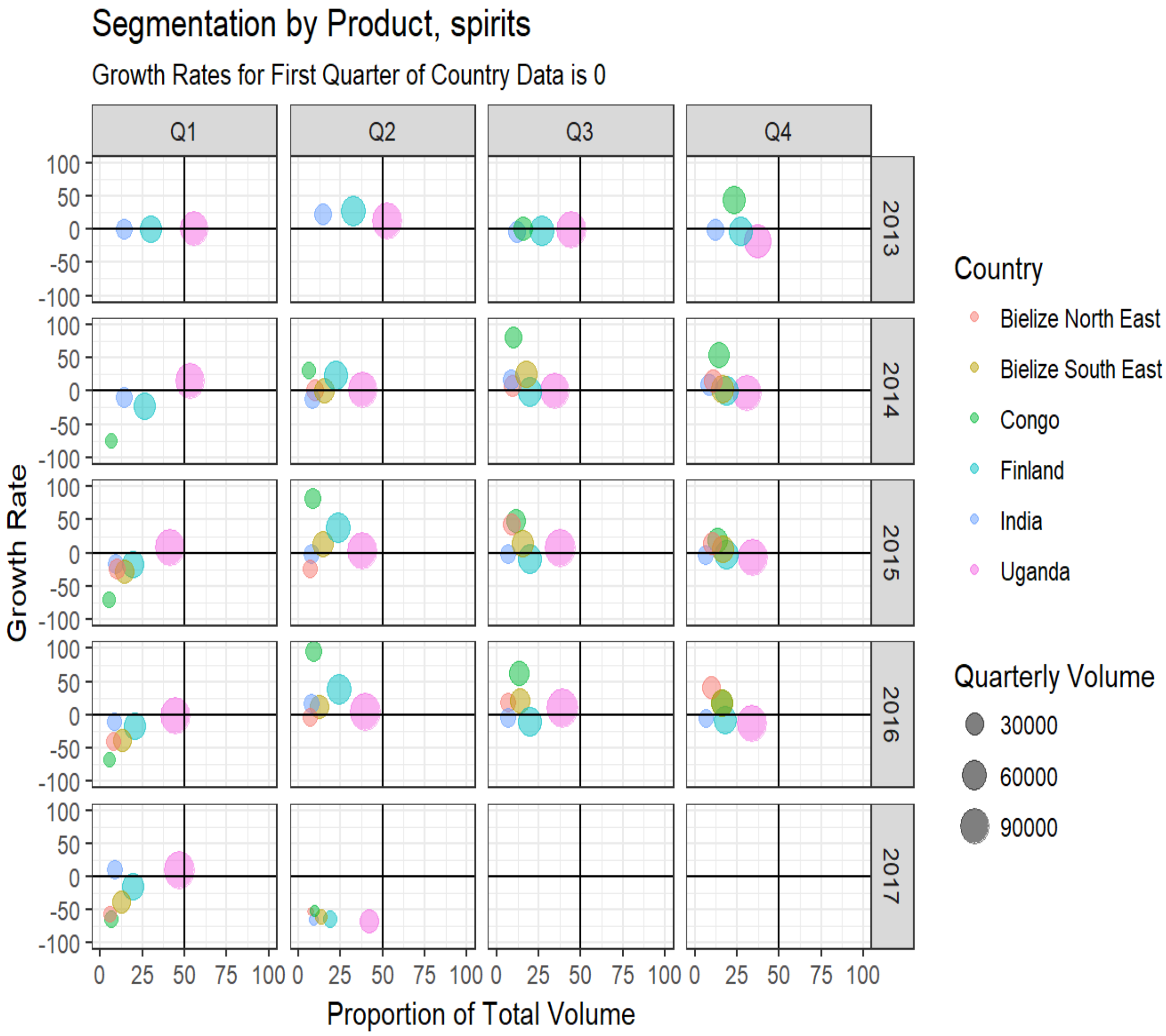
Beer Segmentation



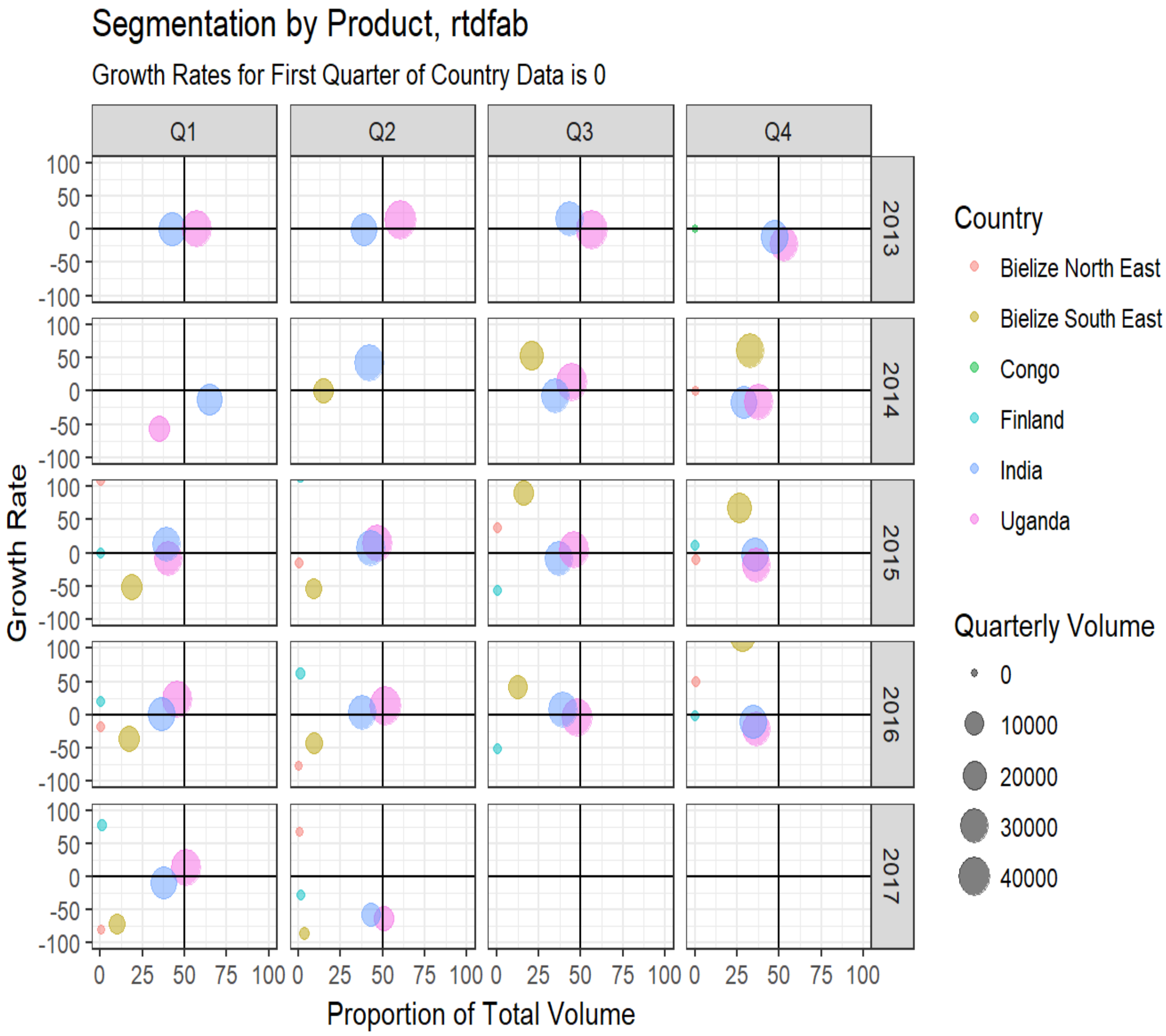
Wine Segmentation



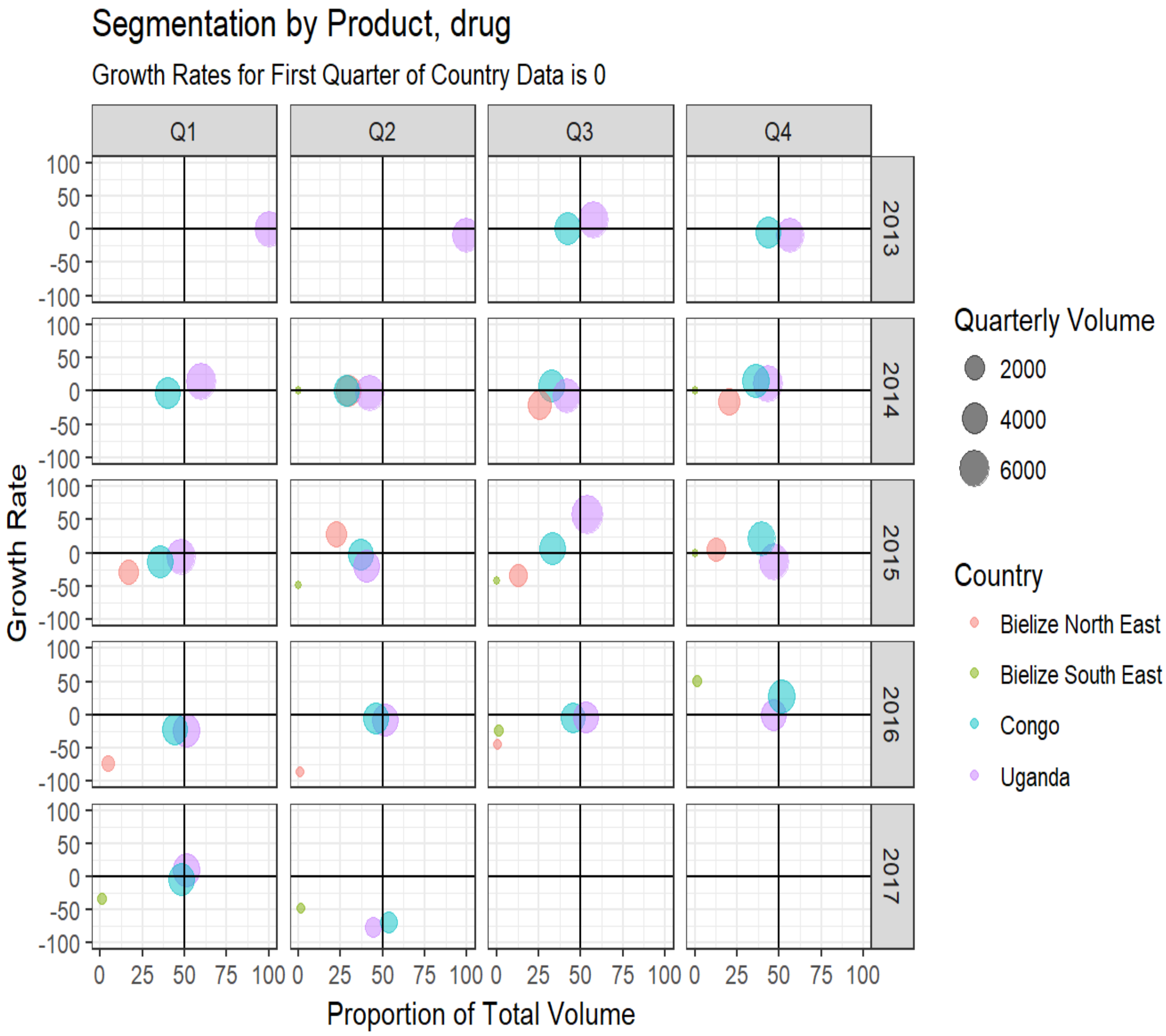
Non Alcoholic Beverage Segmentation



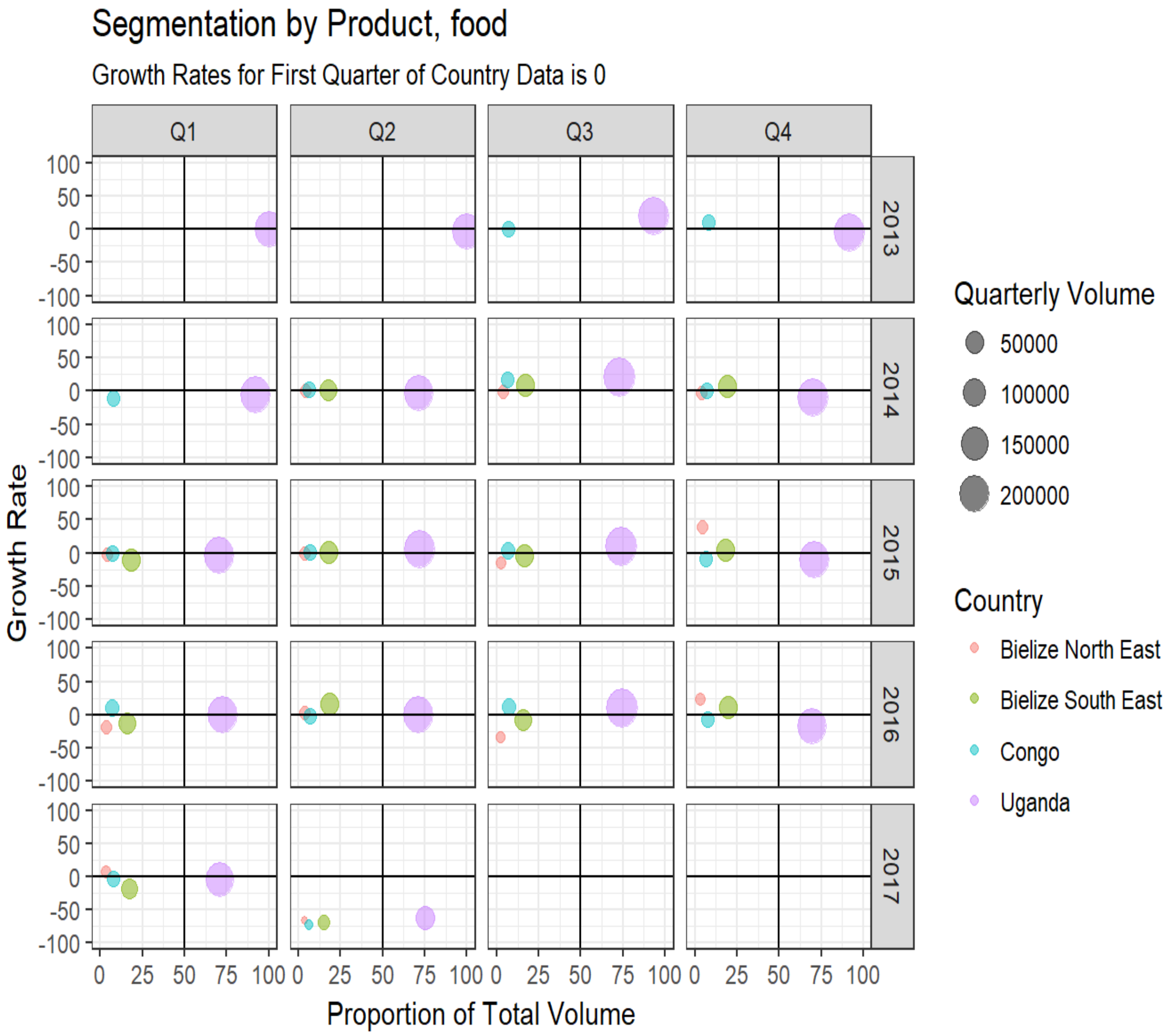
Spirits Segmentation



RTDFAB Segmentation

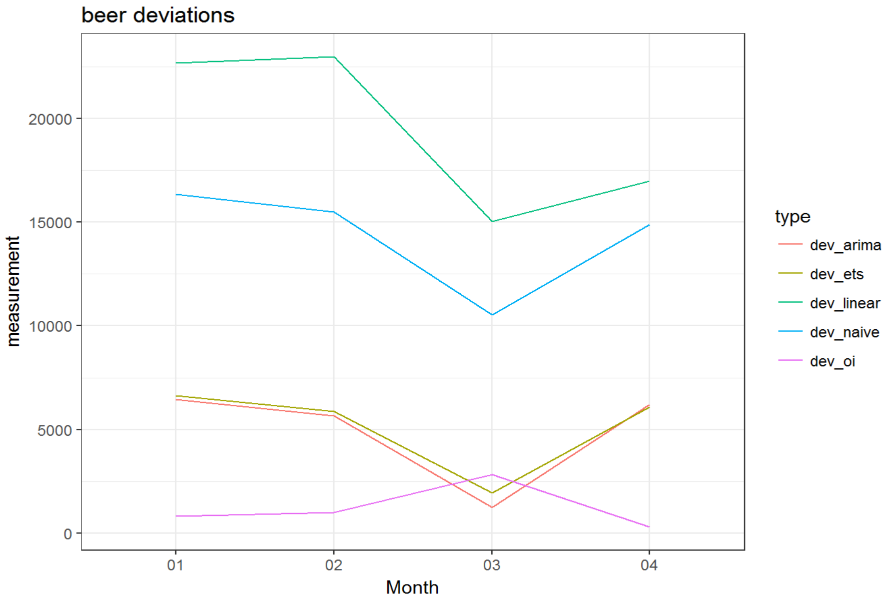


Drugs and Alcohol Segmentation

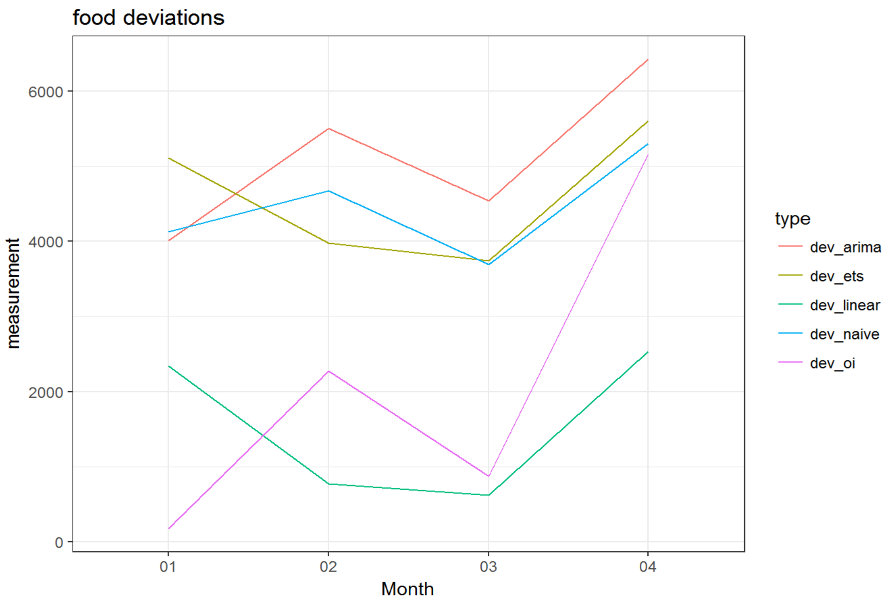


Food Segmentation

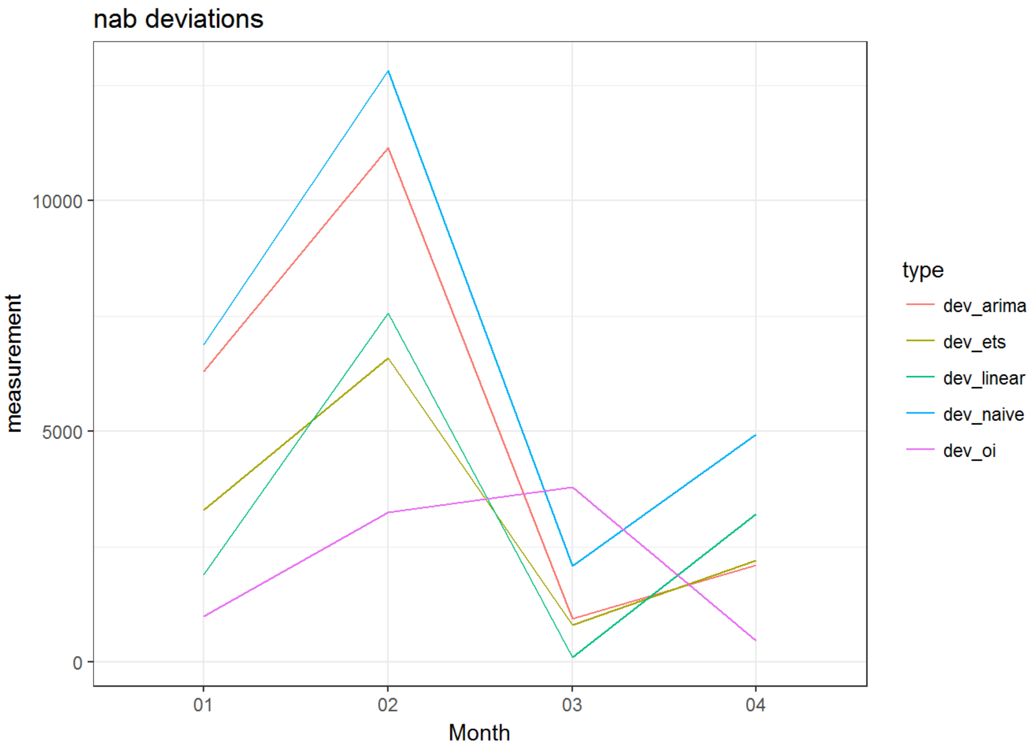
6.10 Forecast Comparison: India



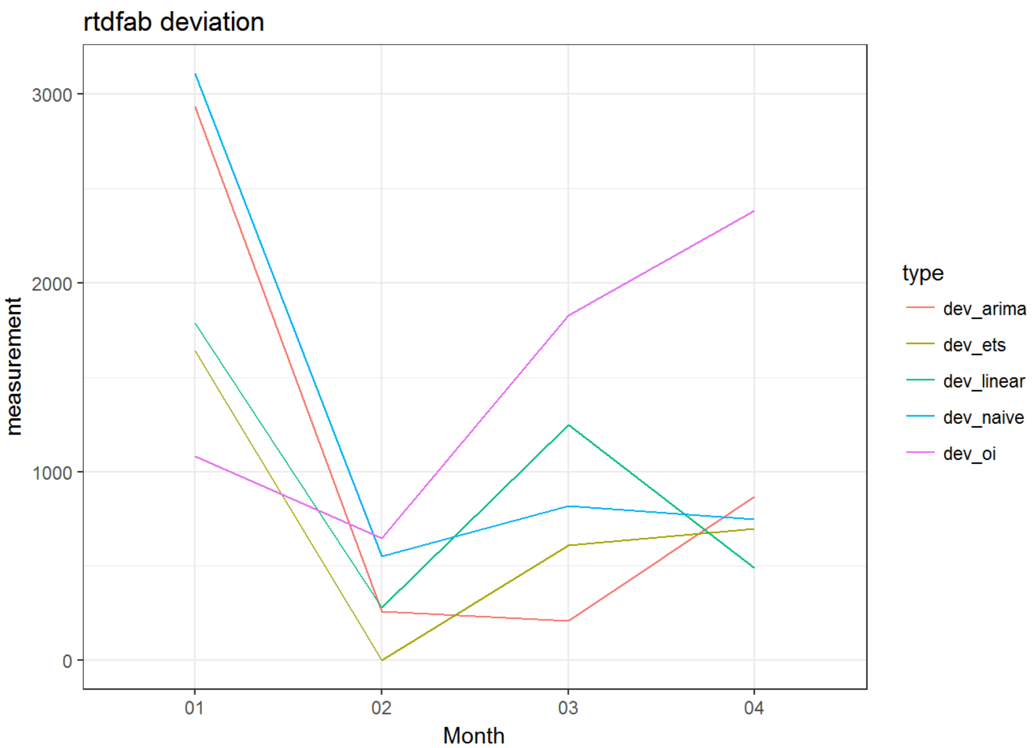
Forecast Comparison for Beer



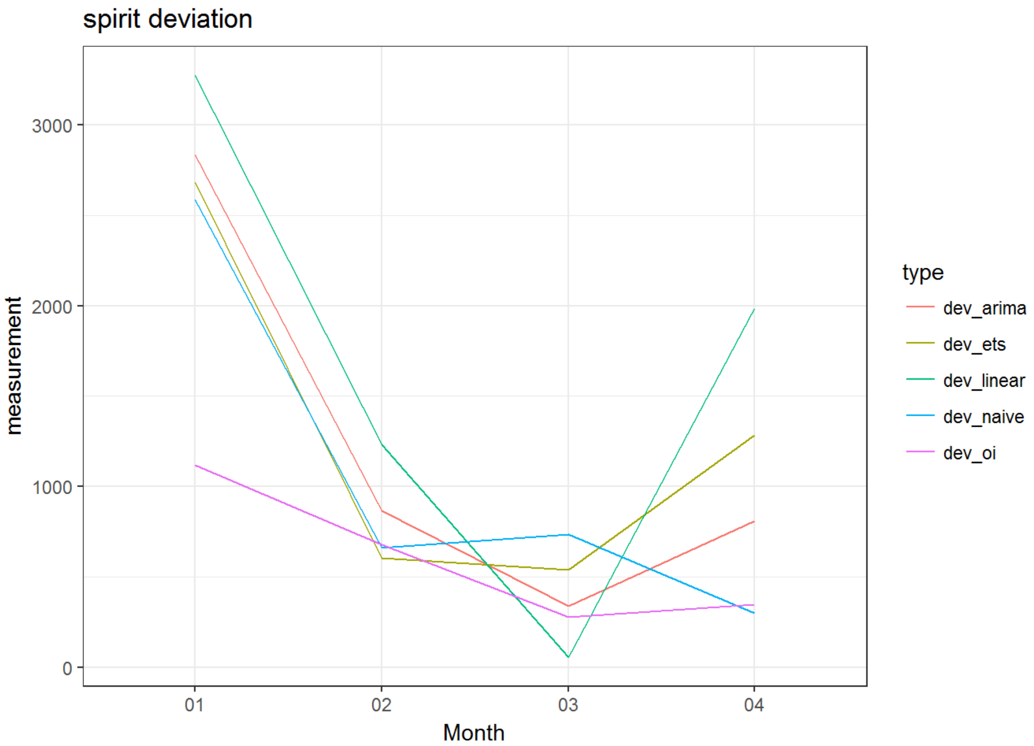
Forecast Comparison for Food (India)



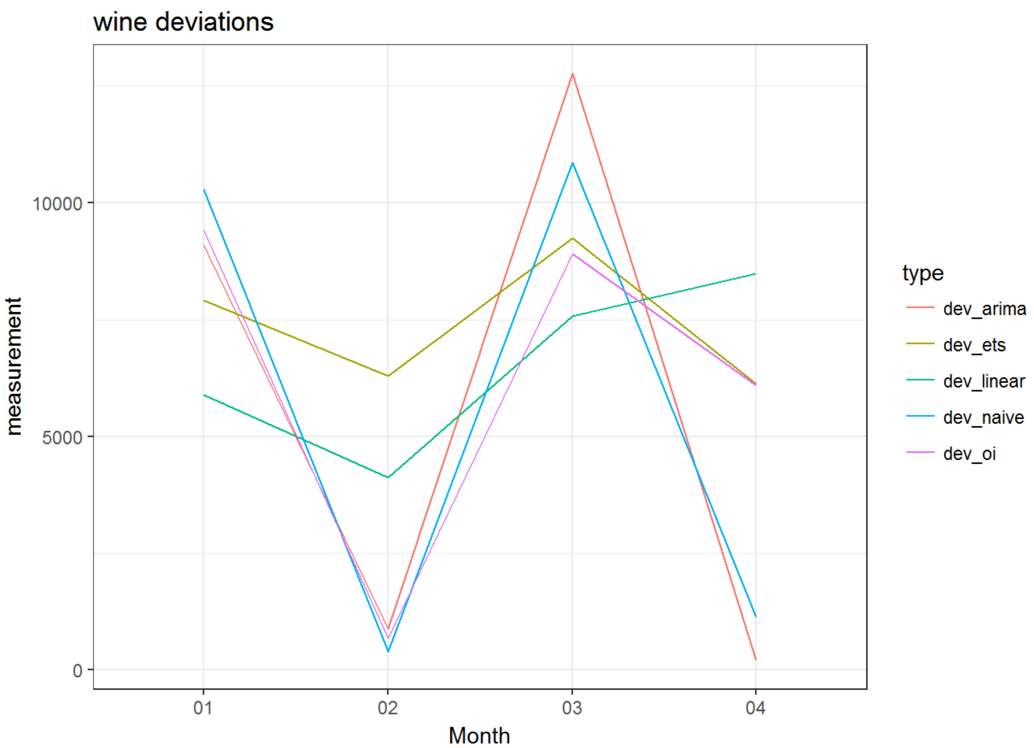
Forecast Comparison for NAB (India)



Forecast Comparison for RTDFAB

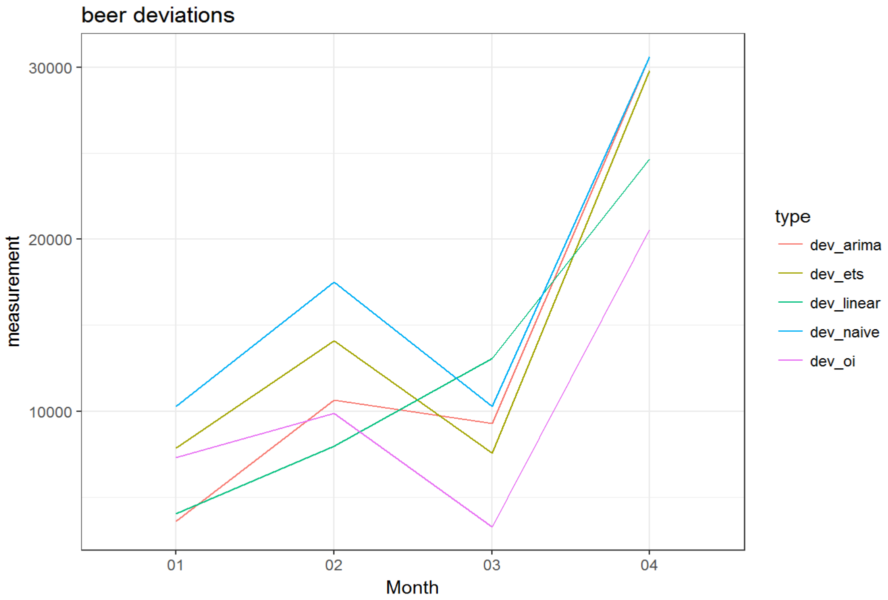


Forecast Comparison for Spirits

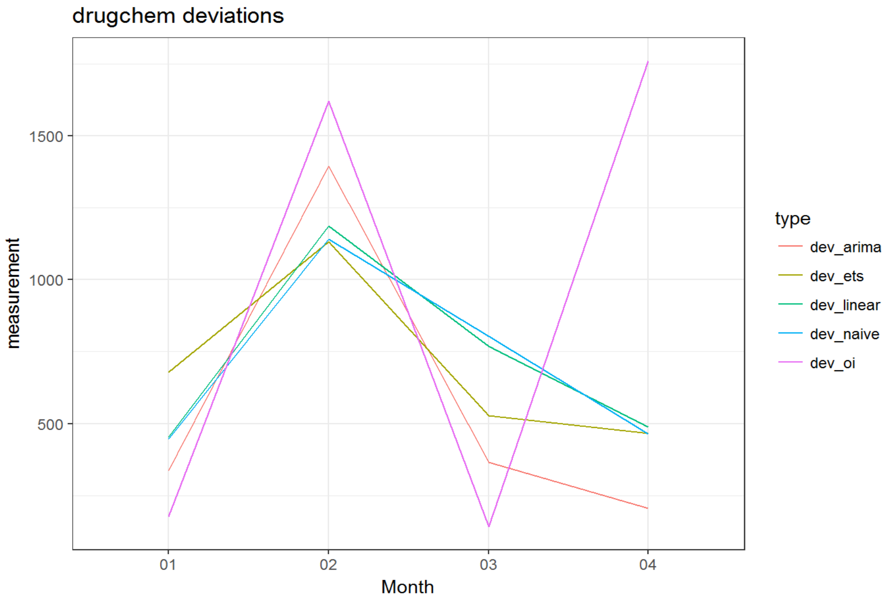


Forecast Comparison for Wine

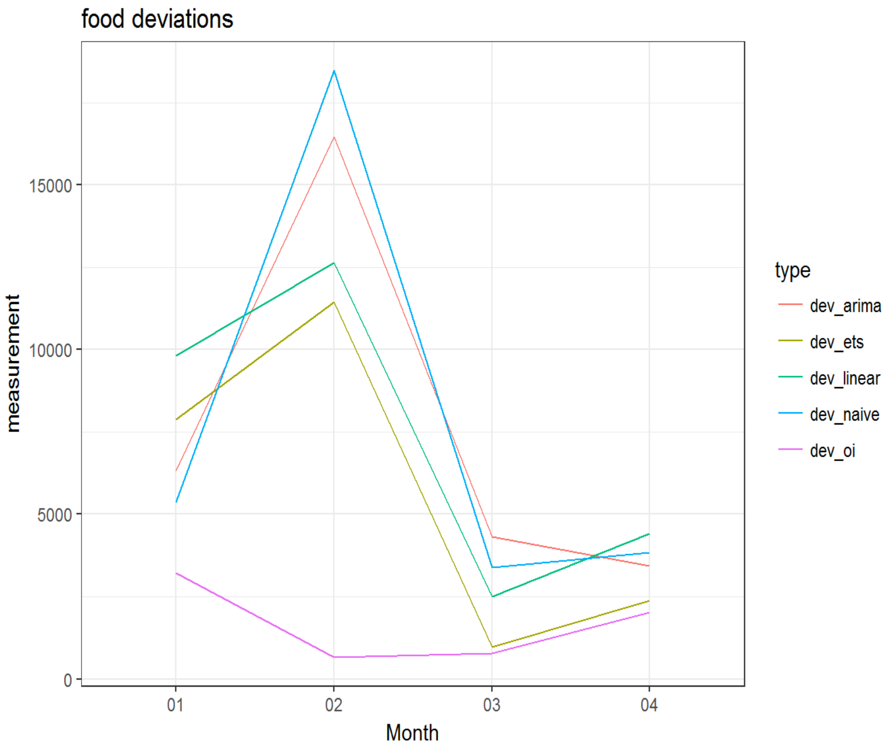
6.11 Forecast Comparison: Uganda



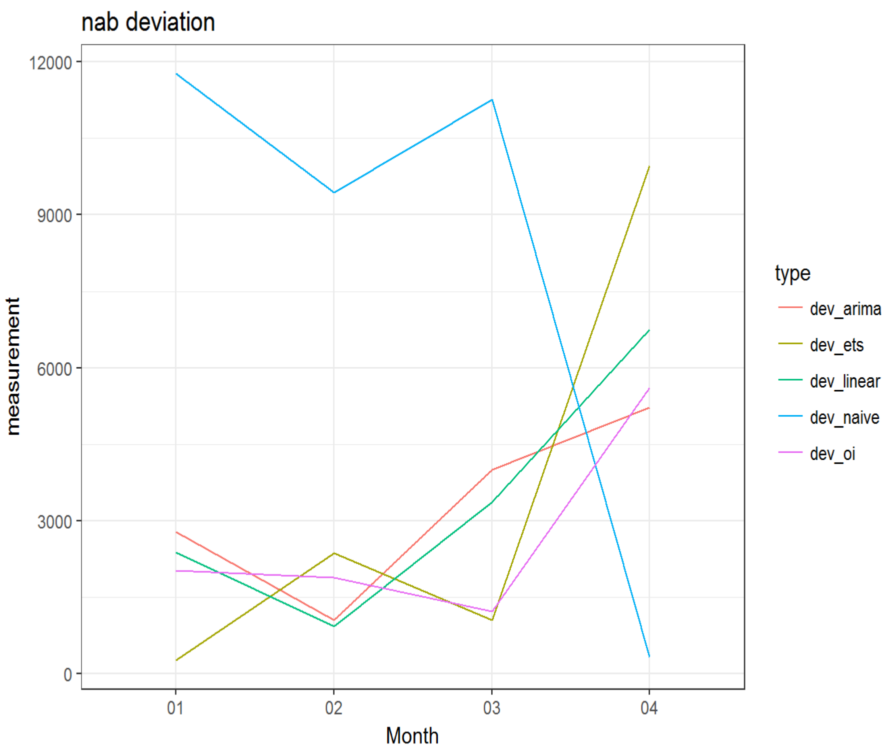
Forecast Comparison for Beer



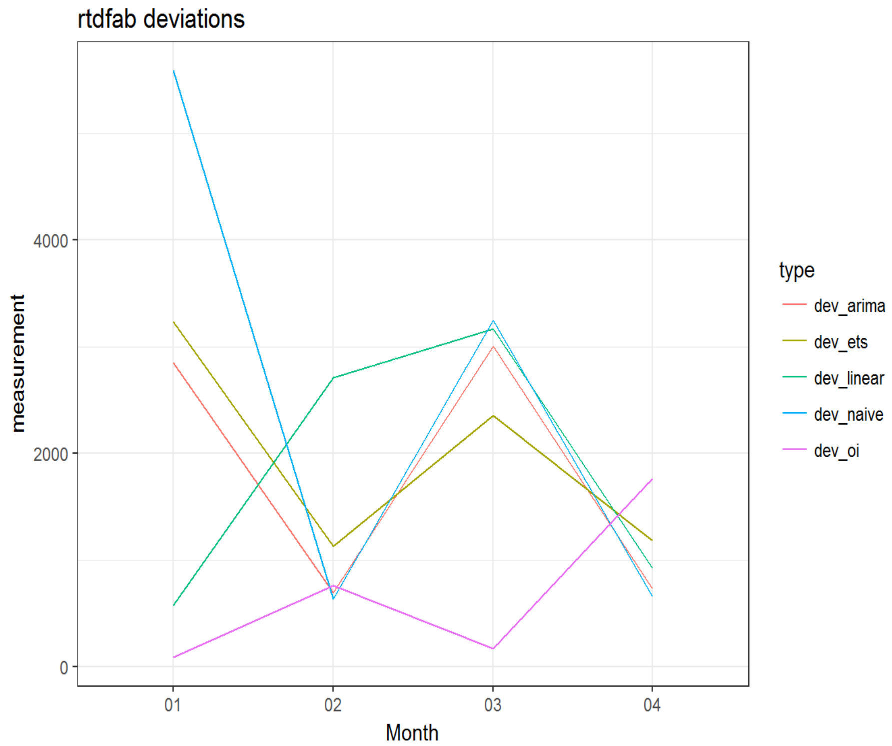
Forecast Comparison for Drugs and Chemicals



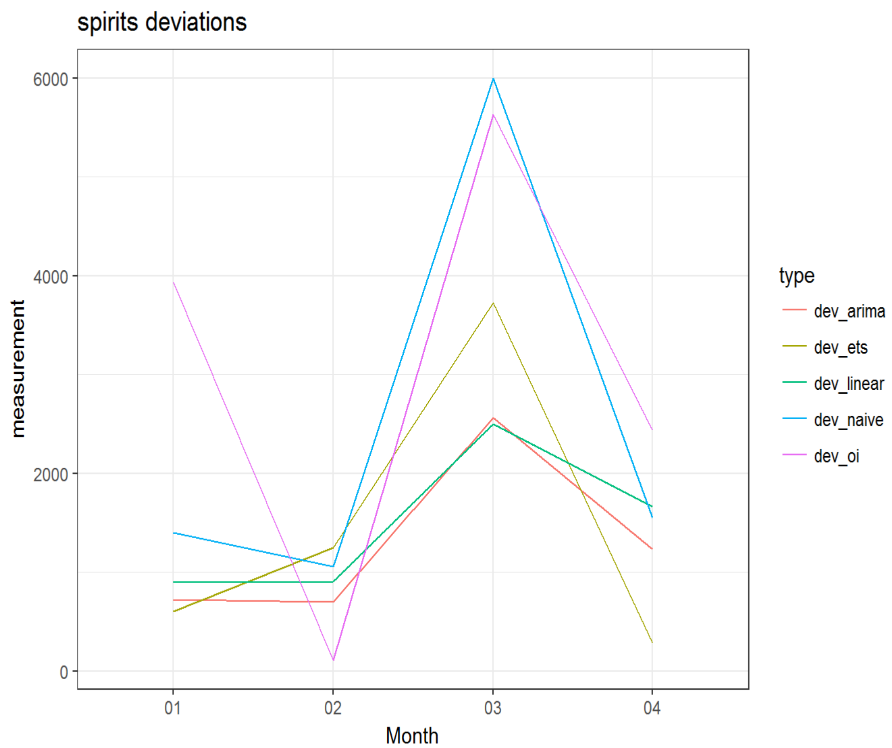
Forecast Comparison for Food



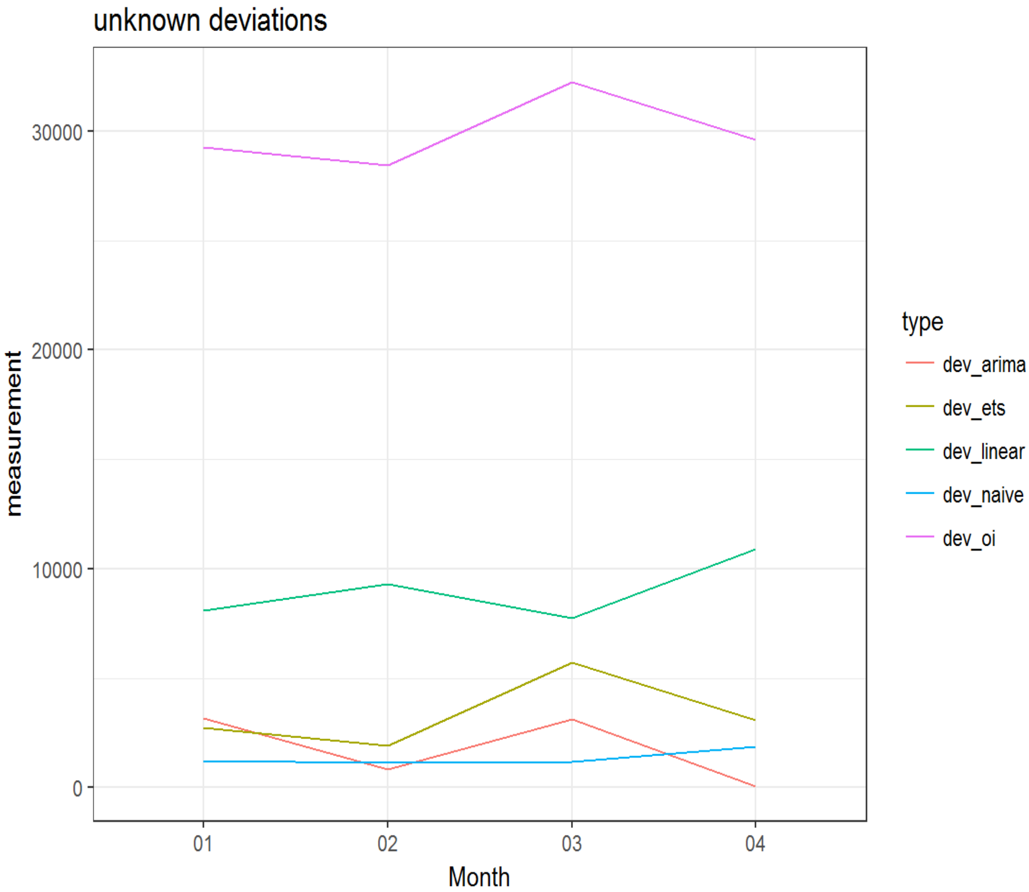
Forecast Comparison for NAB



Forecast Comparison for RTDFAB

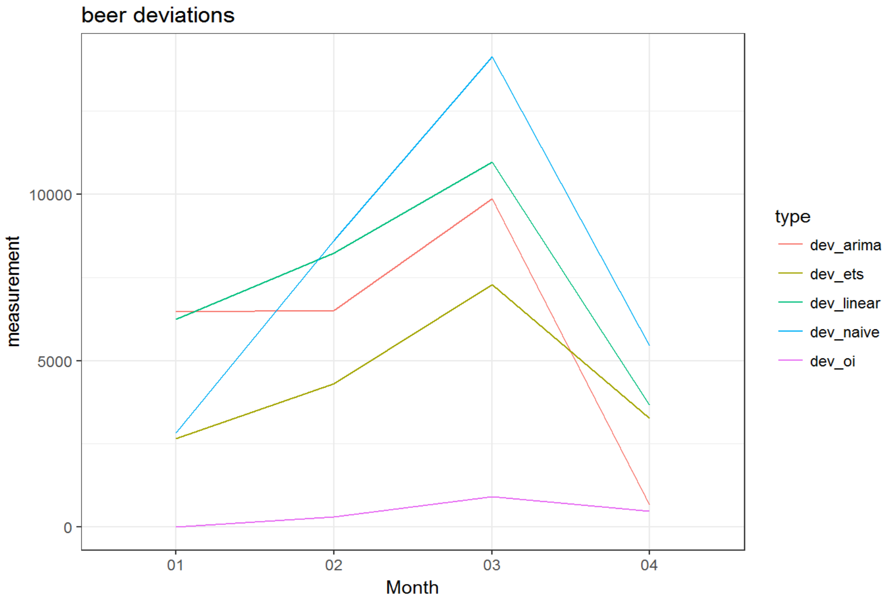


Forecast Comparison for Spirits

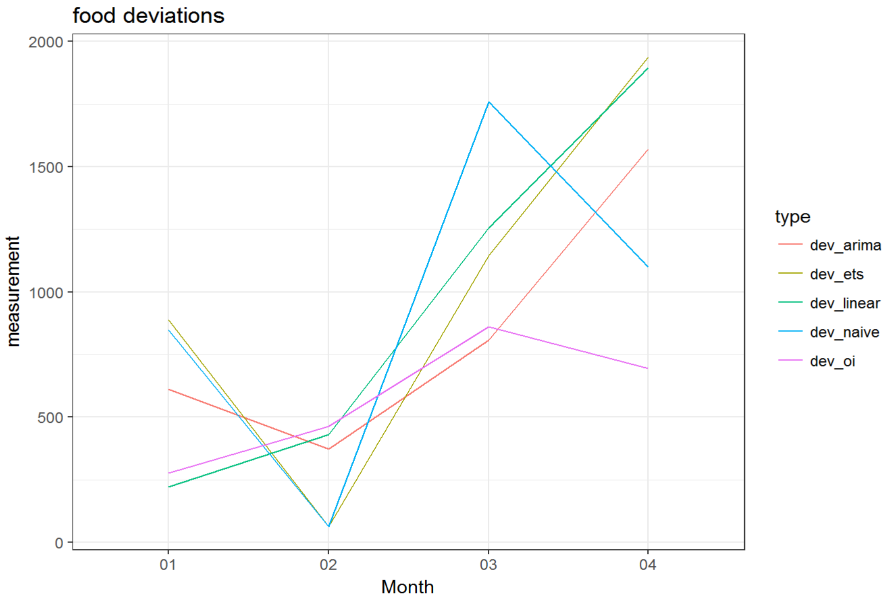


Forecast Comparison for Unknown

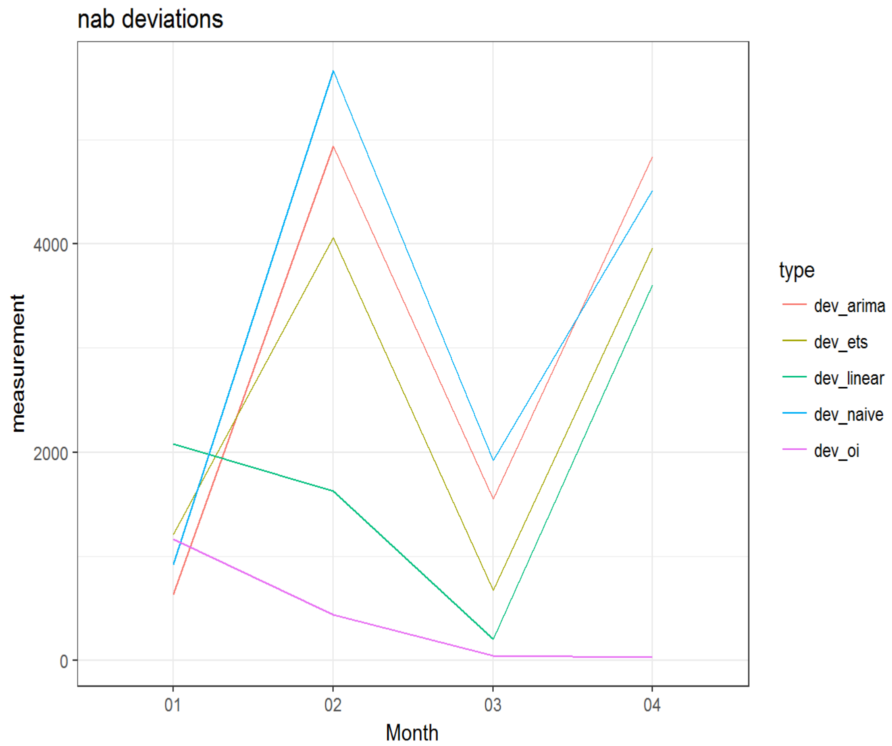
6.12 Forecast Comparison: Congo



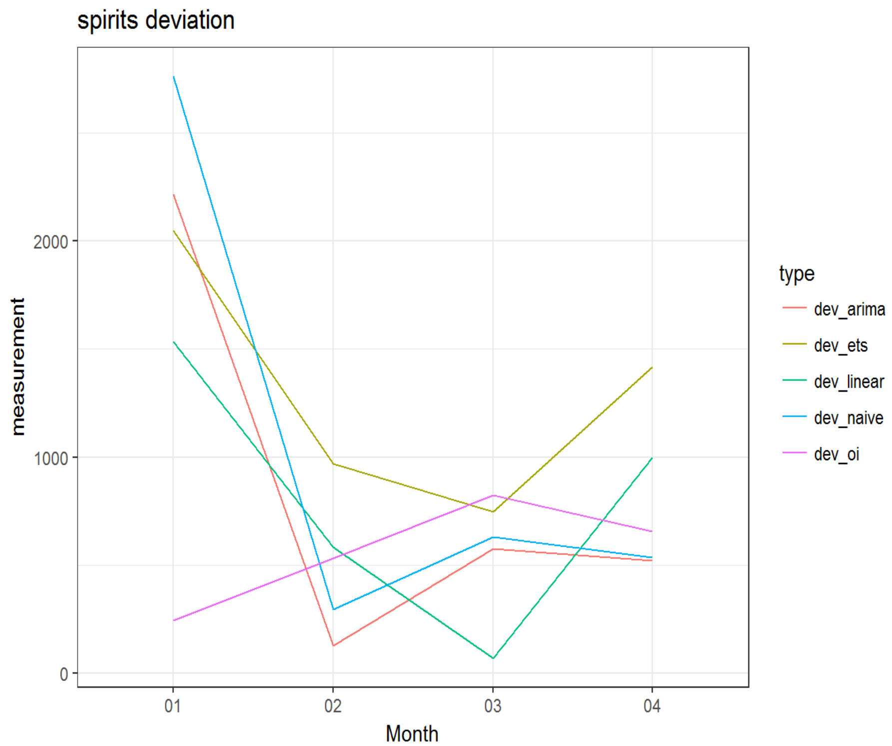
Forecast Comparison for Beer



Forecast Comparison for Food

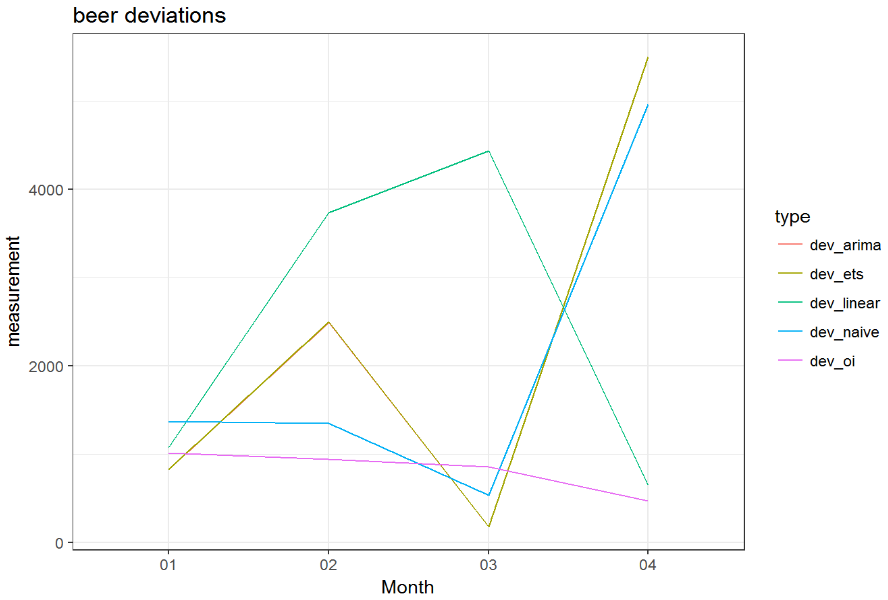


Forecast Comparison for NAB

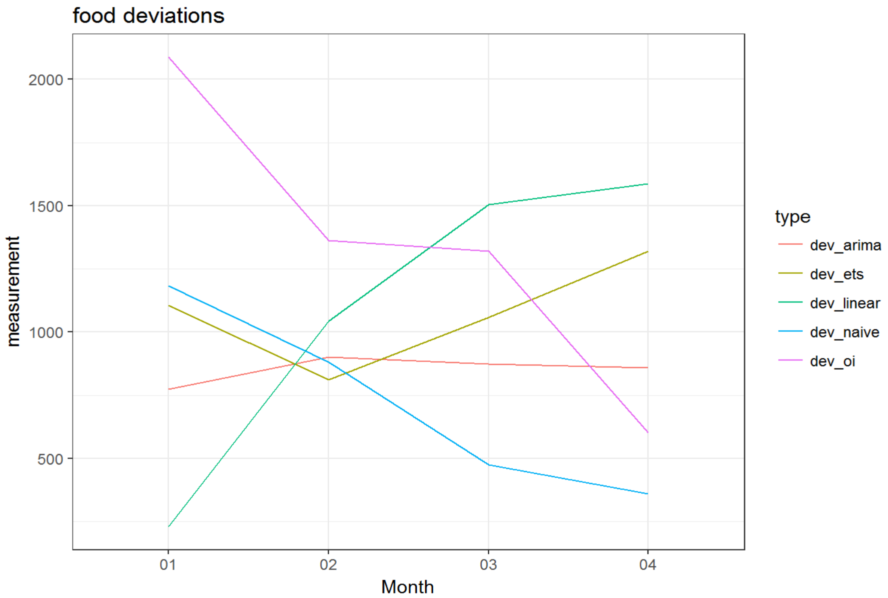


Forecast Comparison for Spirits

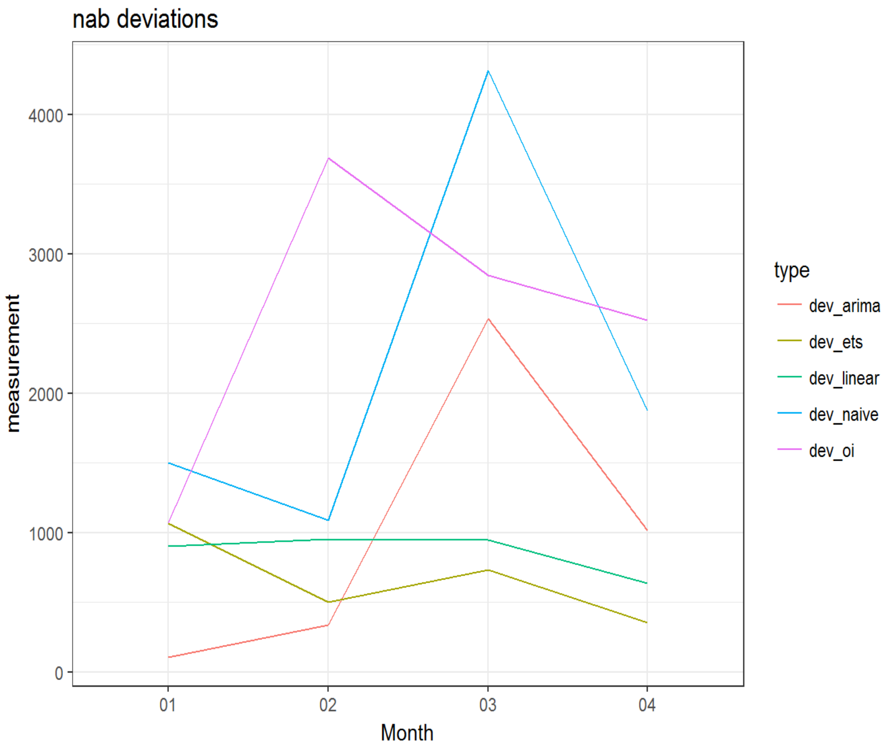
6.13 Forecast Comparison: Finland



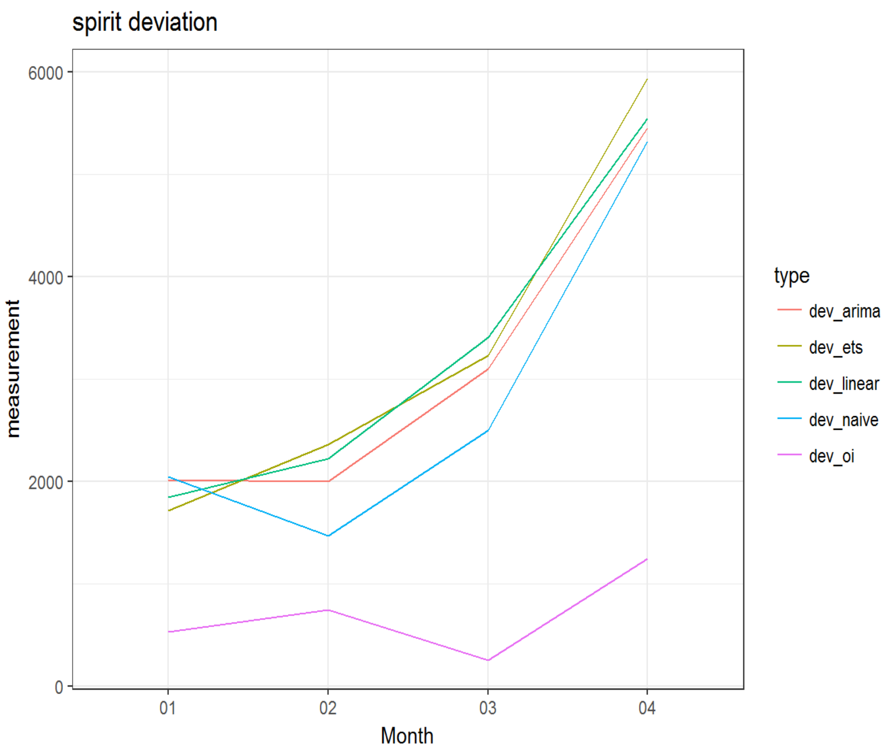
Forecast Comparison for Beer



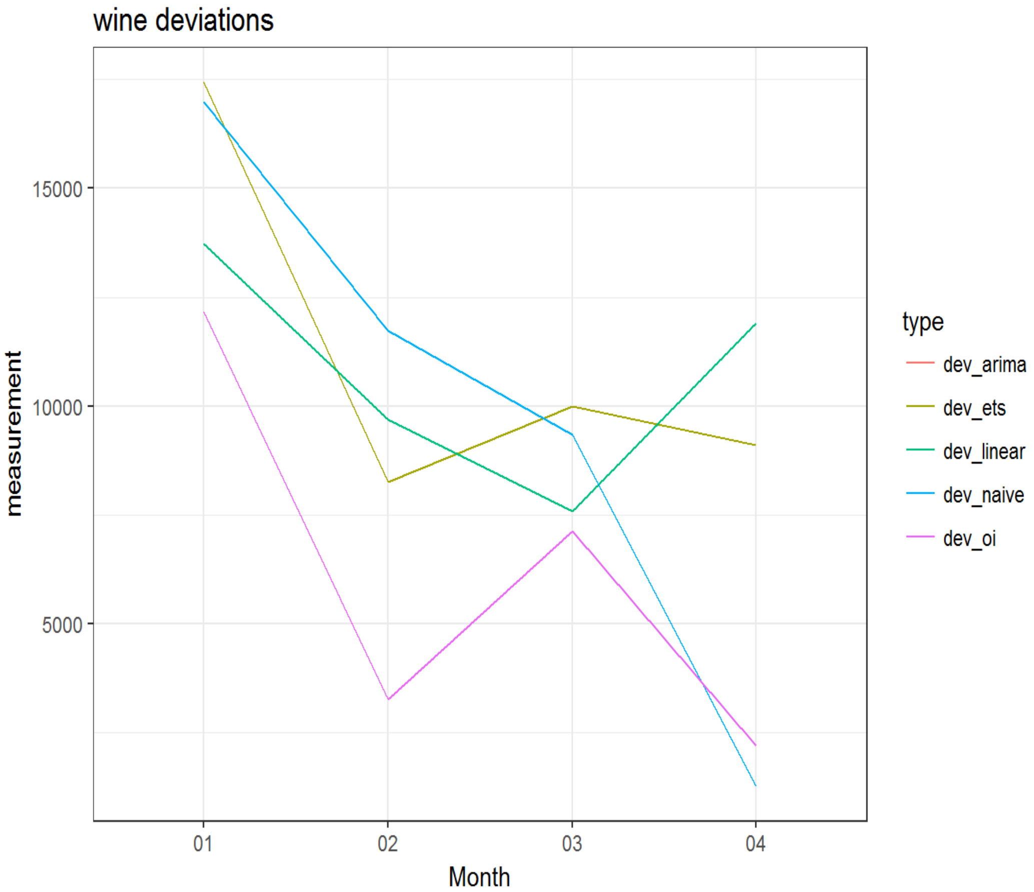
Forecast Comparison for Food



Forecast Comparison for NAB

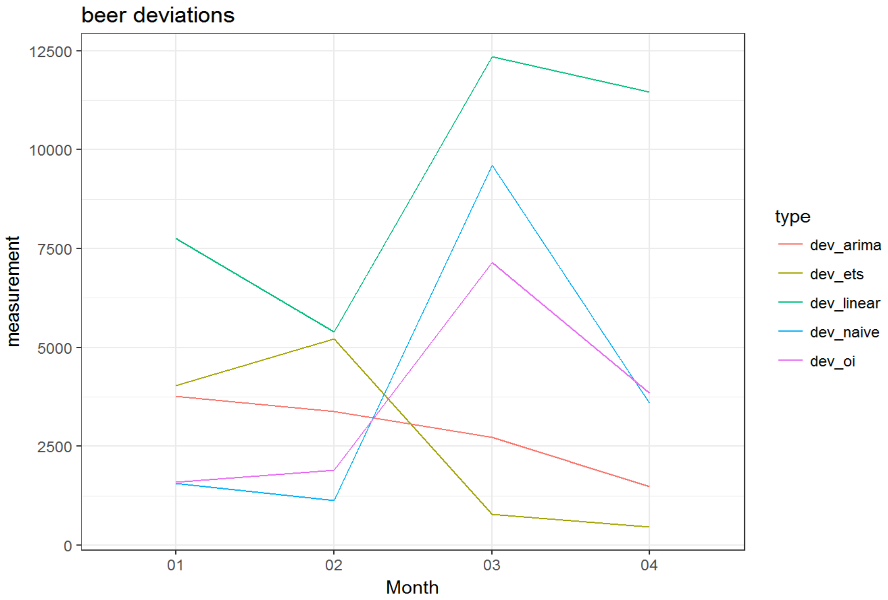


Forecast Comparison for Spirits

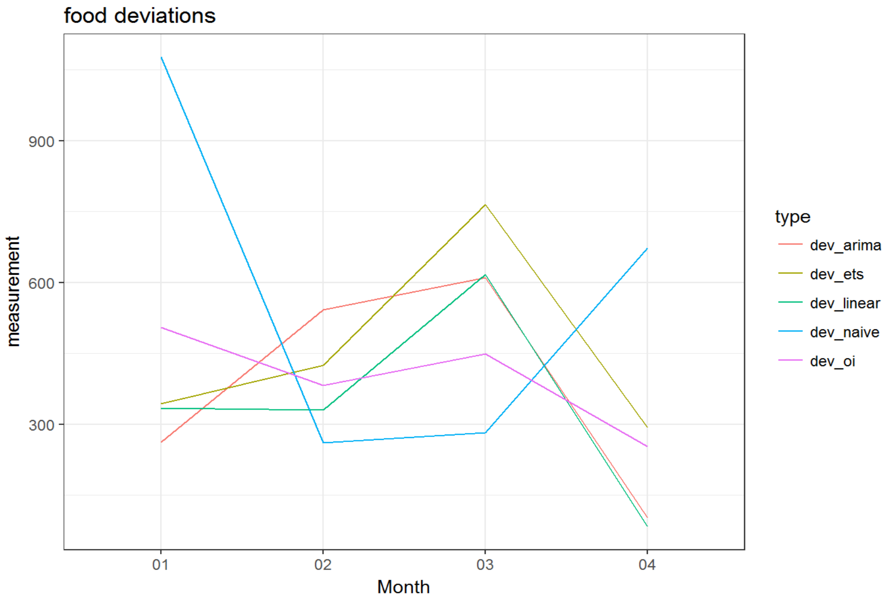


Forecast Comparison for Wine

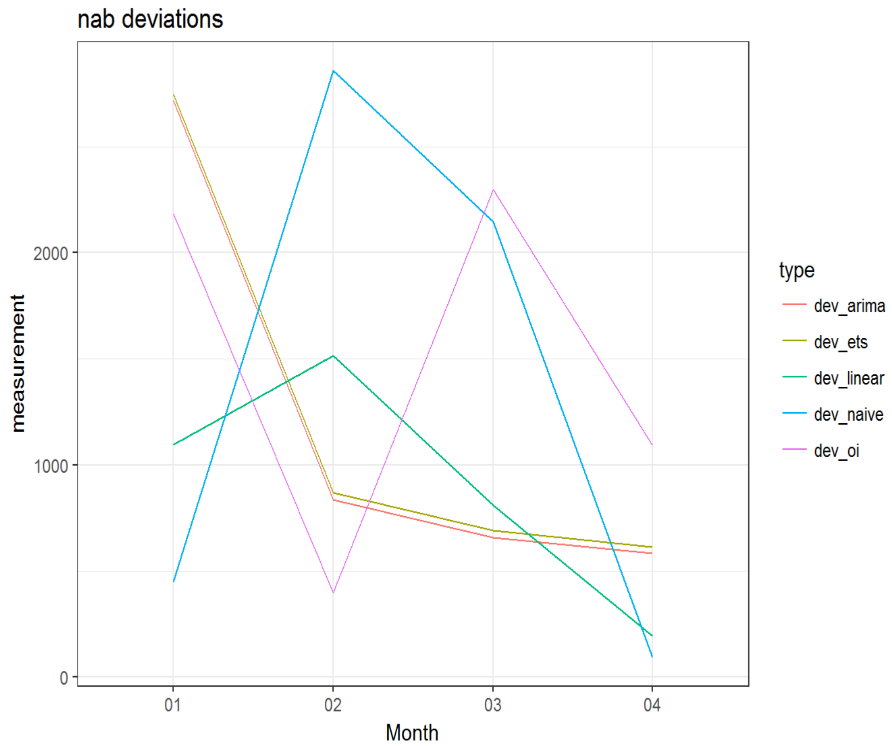
6.14 Forecast Comparison: North East Belize



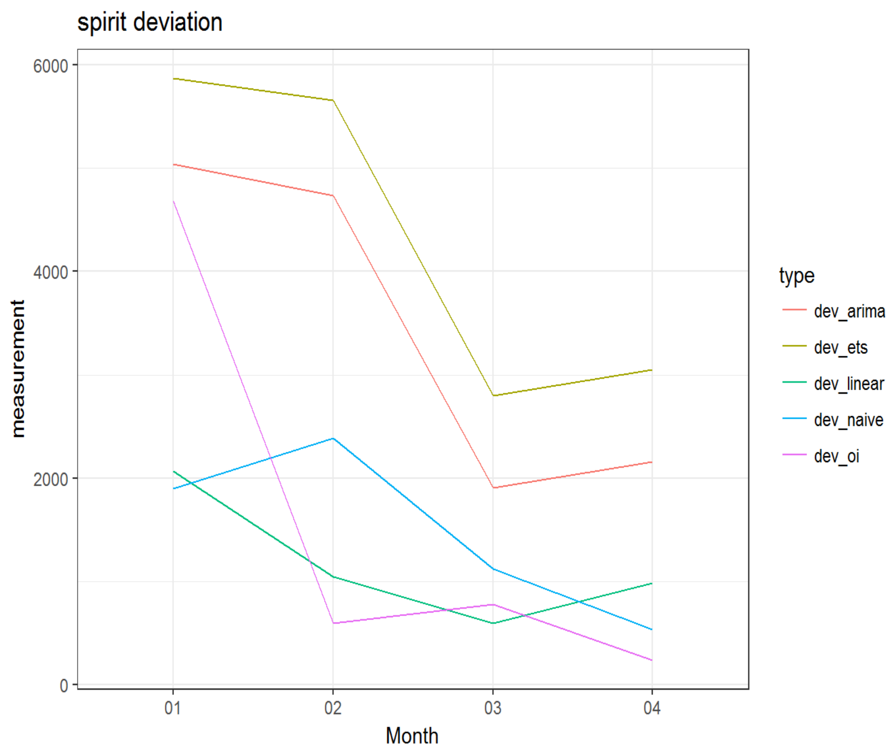
Forecast Comparison for Beer



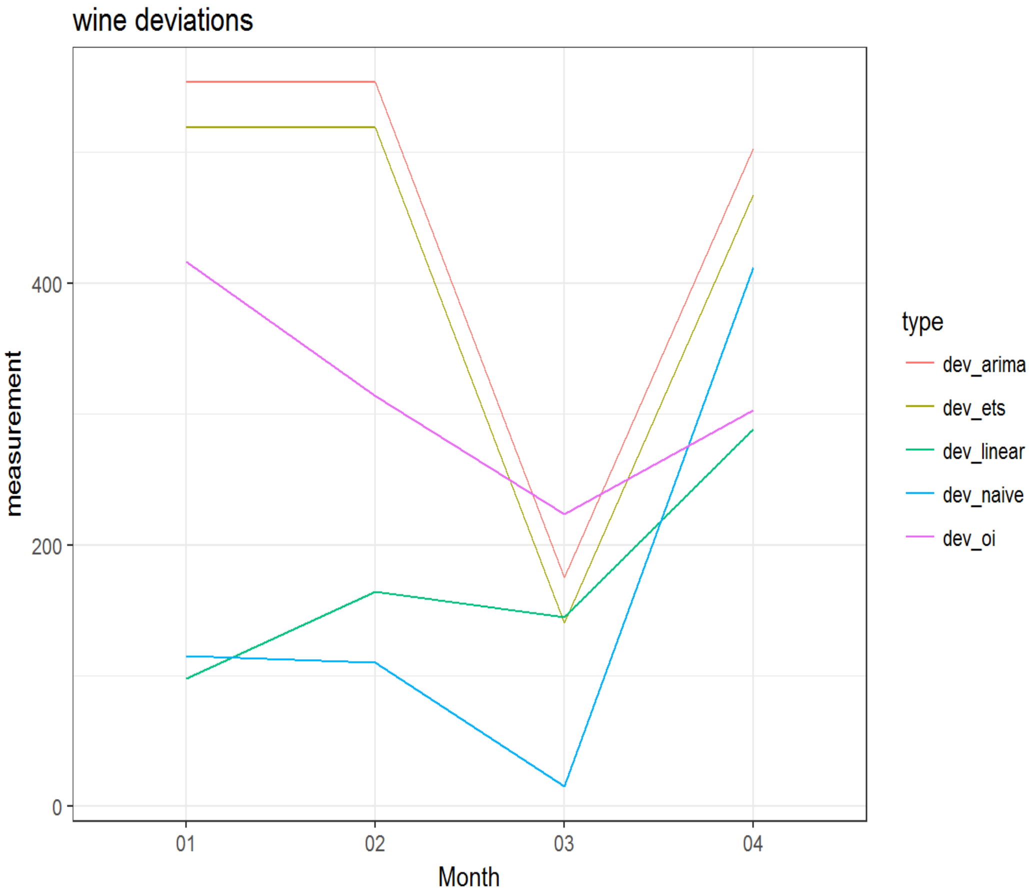
Forecast Comparison for Food



Forecast Comparison for NAB

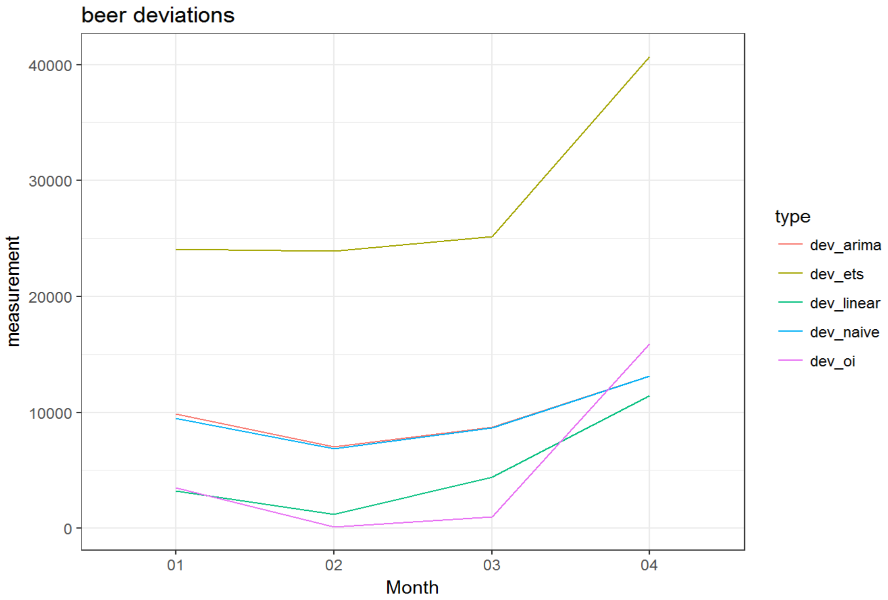


Forecast Comparison for Spirits

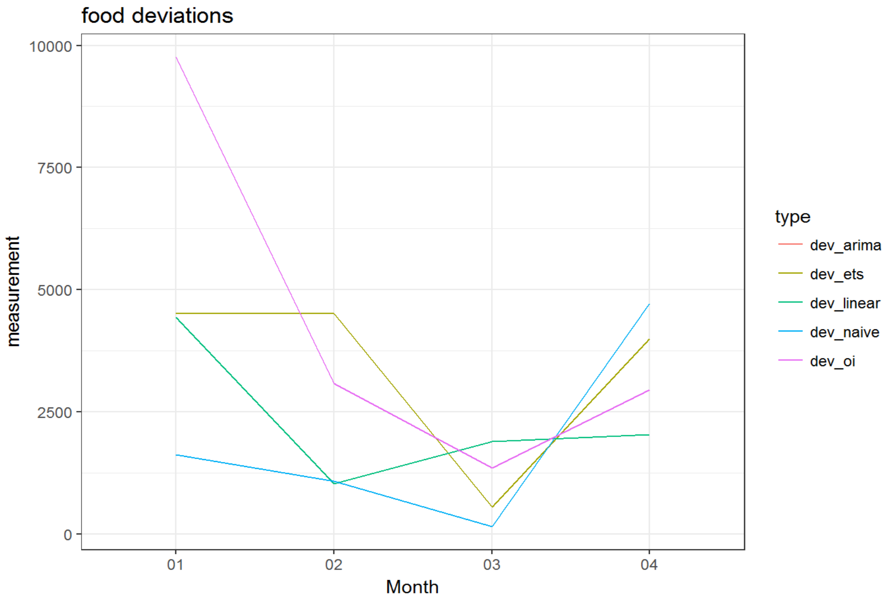


Forecast Comparison for Wine

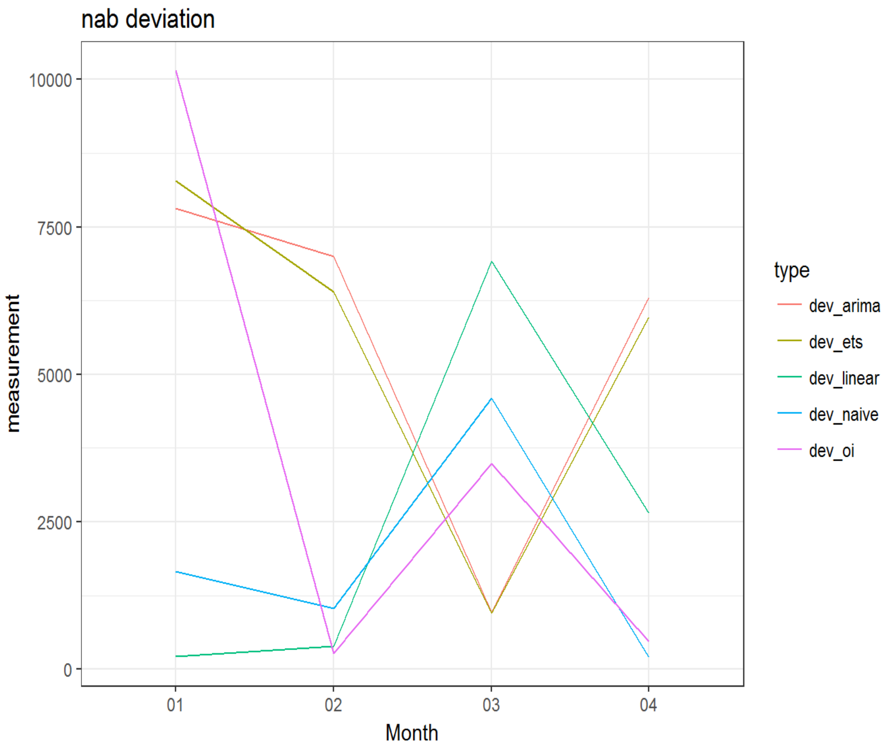
6.15 Forecast Comparison: South East Belize



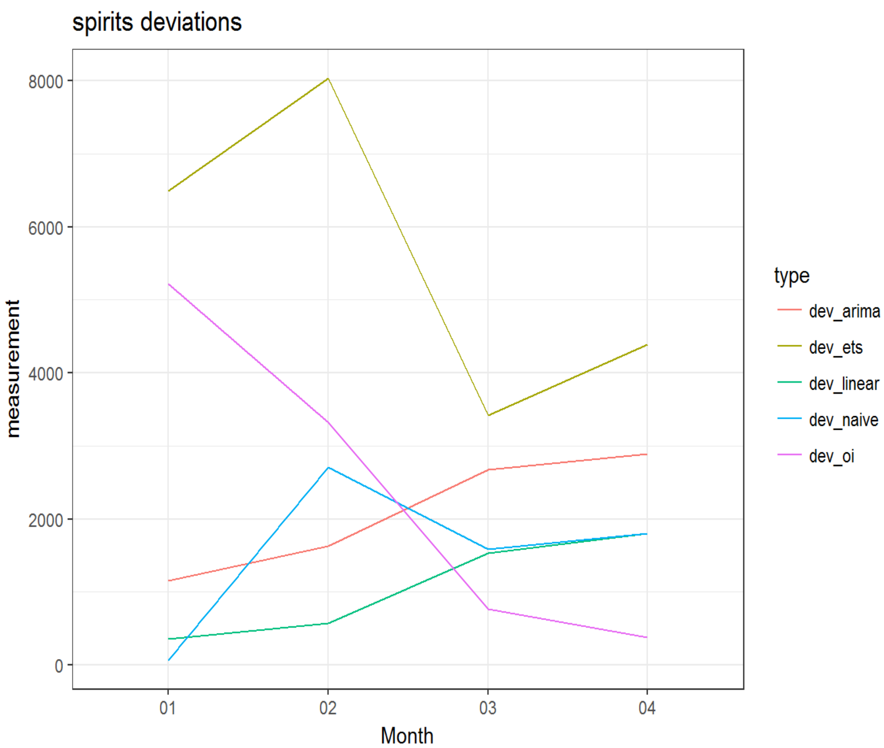
Forecast Comparison for Beer



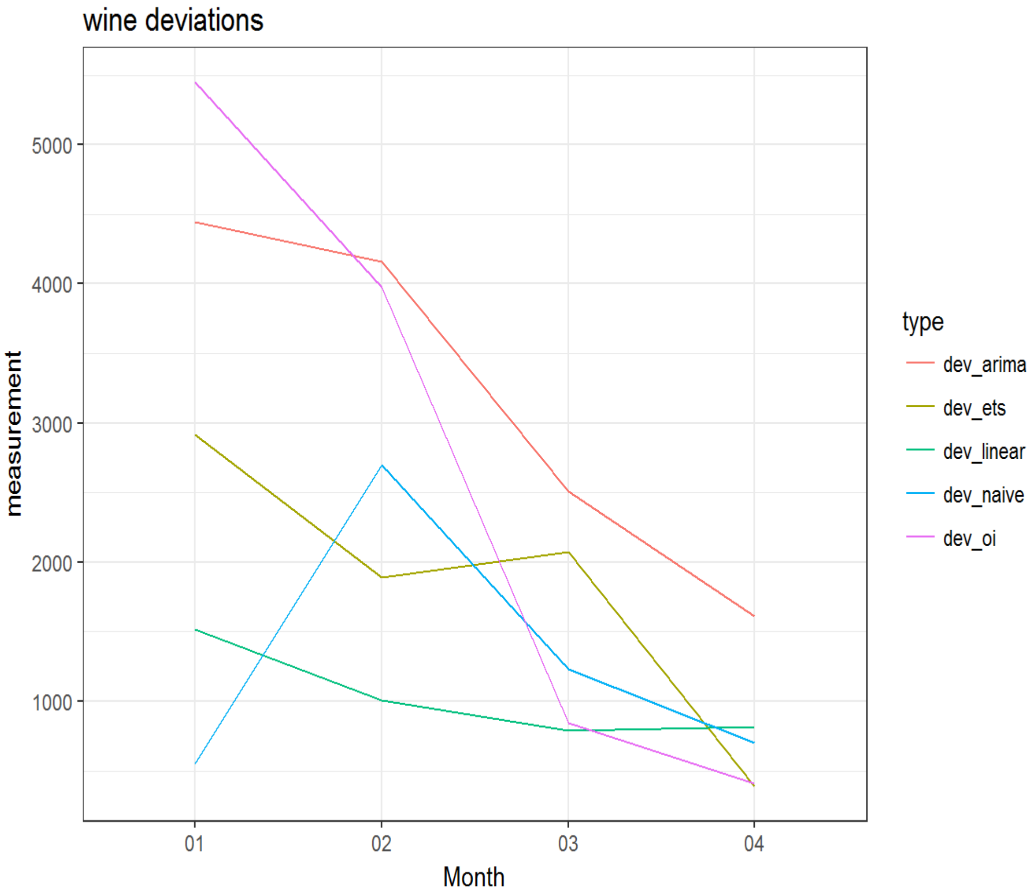
Forecast Comparison for Food



Forecast Comparison for NAB



Forecast Comparison for Spirits



Forecast Comparison for Wine

6.16 List of Tables

Table 1

Customer ID	***Product***	***Total Orders***	***Total Volume***	***Material Type***
8096	nab	401	1042218.52	10
8184	beer	389	348385.58	22
8185	beer	206	261109.96	20
7965	nab	334	235909.32	9
7613	wine	1426	222239	82
7925	wine	445	221070.56	24
7595	wine	3155	172819.98	261
8048	rtdfab	159	169620.68	11
7701	wine	1593	144004.88	106
7681	wine	995	131128.5	66
7773	spirits	541	130180.48	19
8170	beer	545	129684	19
7791	food	449	124209.88	23
7966	nab	855	115418.76	35
7716	wine	1221	113811.62	73
7744	wine	395	109595.82	19
7732	rtdfab	86	100597.12	7
8005	food	745	96689.48	48
8171	beer	504	94729.24	19
8096	rtdfab	51	88347.76	1

Table 2

beer	***food***	***misc***	***nab***	***rtdfab***	***spirits***	***wine***
5.3	17.58	1.36	8.79	1.97	5.3	59.7
beer	***food***	***nab***	***rtdfab***	***spirits***	***wine***	
6.6	19.02	7.98	0.77	4.29	61.35	
beer	***food***	***misc***	***nab***	***rtdfab***	***spirits***	***wine***
3.79	20.49	0.46	8.65	1.06	4.4	61.15
beer	***food***	***nab***	***rtdfab***	***spirits***	***wine***	
3.16	23.01	8.57	2.11	2.71	60.45	

Table 3

Customer ID	***Product***	***Total Orders***	***Total Volume***	***Material Type***
194	beer	2830	1993416.9	246
97	beer	2022	1407549.2	151
98	beer	1548	1111481.8	111
211	beer	1316	923979.4	152
336	beer	447	886839.6	20
96	beer	1483	882505.3	132
48	nab	156	845928.9	6
52	food	433	823596.1	23
340	beer	778	749956.6	47
99	beer	1066	730848.4	79
75	food	957	725984.1	43
341	wine	2027	665774.2	316
193	spirits	3440	612377.6	228
100	beer	639	545610.3	32
366	rtdfab	90	444461.5	2
447	food	627	437022.3	26
198	food	492	378451.8	29
229	beer	140	371491.3	8
1416	beer	56	371401.2	8
86	nab	264	368938.6	28

Table 4

beer	***drugchem***	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
11.03	9.02	7.39	6.27	0.63	6.39	53.63	5.64
beer	***drugchem***	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
15.33	11.06	6.91	1.51	0.25	12.56	44.47	7.91
beer	***drugchem***	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
23.74	6.28	8.17	2.89	0.25	7.04	39.45	12.19
beer	***drugchem***	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
38.39	2.63	9.28	6.9	1.38	5.4	23.96	12.05

Table 5

Customer ID	***Product***	***Total Orders***	***Total Volume***	***Material Type***
3637	nab	622	819857.54	21
3515	beer	325	630824.92	15
3239	beer	195	511320.90	9
2919	wine	2550	493858.50	187
2858	wine	2249	333195.86	165
2872	wine	1014	139793.36	73
2891	wine	944	118588.10	96
2792	wine	1395	117449.62	125
3601	food	240	100374.56	8
3138	spirits	575	99505.72	34
3492	food	125	93550.10	12
3144	spirits	714	91371.58	40
3320	wine	208	88720.12	15
2672	food	3530	86147.84	206
2908	wine	453	85300.40	27
2745	wine	880	83419.34	105
2779	wine	1369	74840.08	78
3131	wine	118	70393.16	9
3127	wine	111	70219.82	13
3646	spirits	237	68788.16	10

Table 6

beer	***food***	***misc***	***nab***	***rtdfab***	***spirits***	***wine***
1.77	1.61	2.9	1.69	0.24	3.14	88.66
beer	***food***	***misc***	***nab***	***rtdfab***	***spirits***	***wine***
0.45	2.88	3.11	1.9	0.08	2.43	89.16
beer	***food***	***misc***	***nab***	***rtdfab***	***spirits***	***wine***
0.76	8.62	2.87	3.1	0.08	5.52	79.05

Table 7

Customer ID	***Product***	***Total Orders***	***Total Volume***	***Material Type***
2436	beer	471	327316.83	27
2428	nab	991	190288.98	103
2421	nab	1594	173827.56	73
2450	spirits	667	136963.83	79
2482	unknown	43	111657.35	2
2420	nab	1110	109219.86	45
2419	nab	1058	100951.38	47
2444	spirits	468	81292.20	43
2438	beer	166	67250.68	11
2123	beer	46	57548.51	7
1618	beer	10	53368.21	4
2439	beer	152	51866.03	12
2431	nab	879	51267.17	34
2424	food	999	50272.94	88
2426	food	564	45472.52	31
2594	nab	80	44681.18	6
2425	food	184	42222.61	9
2453	spirits	207	39708.46	16
2430	nab	951	31493.78	47
2360	spirits	250	29425.73	40

Table 8

beer	***Beverage***	***drugchem***	***food***	***misc***	***nab***	***spirits***	***unknown***		
0.59	3.53	7.65	12.94	0.59	11.76	8.82	54.12		
beer	***Beverage***	***drugchem***	***food***	***misc***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
2.94	1.76	8.82	17.06	2.35	11.76	0.59	8.24	45.88	0.59
beer	***Beverage***	***drugchem***	***food***	***misc***	***nab***	***spirits***	***unknown***		
3.53	1.18	12.35	14.12	0.59	10	12.35	45.88		
beer	***drugchem***	***food***	***nab***	***spirits***	***unknown***				
8.88	12.43	17.16	11.24	20.71	29.59				

Table 9

Customer ID	***Product***	***Total Orders***	***Total Volume***	***Material Type***
1618	beer	348	307328.61	21
1850	spirits	228	100237.75	14
1689	spirits	215	66036.94	14
1888	beer	147	53276.33	9
1761	nab	111	46711.99	12
1742	beer	142	37140.98	9
1645	spirits	120	36999.95	9
1618	unknown	111	34997.29	3
2149	food	83	34939.17	5
1779	beer	96	28145.07	7
2166	beer	73	21028.43	5
2135	spirits	53	17301.05	4
1850	unknown	111	17254.75	3
1656	spirits	153	16622.22	14
2143	nab	64	14869.00	3
1604	nab	49	14397.27	2
2167	beer	46	13587.60	3
1977	spirits	178	12422.49	10
2147	food	53	11023.99	6
1928	beer	42	10996.36	4

Table 10

beer	***drugchem***	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
9.77	27.07	17.29	9.77	1.5	5.26	27.82	1.5
beer	***drugchem***	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
3.79	30.3	12.12	8.33	0.76	6.82	34.85	3.03
beer	***drugchem***	***food***	***nab***	***spirits***	***unknown***	***wine***	
6.82	31.82	18.94	5.3	9.09	25.76	2.27	
beer	***drugchem***	***food***	***nab***	***spirits***	***unknown***	***wine***	
6.82	31.82	18.94	5.3	9.09	25.76	2.27	

Table 11

Customer ID	***Product***	***Total Orders***	***Total Volume***	***Material Type***
1618	beer	467	727600.97	65
1653	beer	331	390837.13	34
1620	beer	385	168330.53	27
1609	food	296	148150.29	15
1618	nab	241	139772.48	25
1711	beer	200	122261.14	17
1656	wine	172	105896.69	23
1621	beer	273	92354.61	27
1618	unknown	111	91859.71	3
1667	nab	196	85320.76	15
1656	rtdfab	74	81956.17	7
1689	spirits	324	79357.47	23
1603	food	268	68654.78	27
1661	food	526	65112.42	86
1665	nab	162	63323.74	25
1616	spirits	317	59884.75	33
1645	spirits	267	58912.70	23
1656	spirits	314	55475.23	31
1653	unknown	111	47560.91	3
1602	spirits	263	45438.71	18

Table 12

beer	***drugchem***	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
6.82	2.6	9.74	7.79	3.57	8.12	57.14	4.22
beer	***drugchem***	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
16.29	2.93	12.7	7.82	4.89	10.42	36.48	8.47
beer	***drugchem***	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***
12.05	0.98	17.26	12.05	3.91	9.45	37.79	6.51
beer	***food***	***nab***	***rtdfab***	***spirits***	***unknown***	***wine***	
13.36	19.87	15.64	4.56	11.4	25.73	9.45	