Forecast Drayage Demand

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ABSTRACT

Drayage, which involves transporting goods from ports to drop facilities, has become increasingly difficult to predict due to the volatility of macroeconomic conditions. As a result, our sponsor company, a third-party logistics (3PL), sought to identify the key macroeconomic indicators that affect drayage volume and whether these indicators vary by port. To do this, the study utilized SARIMAX, a time-series forecasting method that can incorporate external variables and capture trends, seasonality, and cycles in the data. The study revealed that Advanced Retail Sales, New Housing Units Built, Total Vehicle Sales, Unemployment Rate, Total Nonfarm, and CPI: Fuel were significant indicators on forecasting drayage volume. Moreover, the study found that these indicators varied across different ports. Leveraging SARIMAX and these macroeconomic indicators resulted in an average 21% increase in forecast accuracy compared with the seasonal Naïve method, which can help the company better allocate drayage capacity, improve resource planning, and reduce associated cost.

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Pu Gao

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1 Introduction

1.1 Company Background

Nearly all industries have faced severe supply chain challenges due to the COVID-19 pandemic and subsequent lockdowns across the globe. It is vital for companies to understand the factors that drive business disruptions and complexities as well as how they affect business decision-making processes.

During the COVID-19 pandemic, business inventories dropped to near-historic lows, leading companies to pay a premium on shipping to get products on shelves at nearly any cost. Unquestionably, the chaos and volatility in volume also posed a big challenge to our sponsor company. Our sponsor company, a freight brokerage and third-party logistics (3PL) service company, provides full-truckload, less-than-truckload, final-mile, drayage, and warehousing solutions and services. Drayage is one service that they provide, this is the over-the-road component of the international transportation of goods from the destination port to a drop facility (50-100 miles). It plays an important role in enabling the smooth and efficient transfer of goods from ports to customers through the end-to-end supply chain process.

1.2 Problem Statement

As the volume of U.S. exports and imports becomes more volatile due to the COVID-19 Pandemic and economic uncertainty, our sponsor company is experiencing more difficulty predicting the drayage volume of the international transportation of goods at various ports.

Therefore, the company is interested in understanding how various factors (geographical, economic, and geopolitical) influence drayage volume at different ports. Understanding the weight of these factors can help the company allocate the right drayage volume capacity at each port they serve.

This capstone addresses the following questions:

1) What are the leading indicators that affect drayage volume at different ports?
2) How do these indicators help in predicting the volatility in drayage volume? Do they differ by port?
3) How can our sponsor company better allocate the right drayage capacity to different ports after understanding the weight of these indicators?

1.3 Scope

The project's overall goal is to understand different factors that affect the drayage volume and develop a predictive model to facilitate the company in allocating the right drayage capacity to ports based on various factors. We built tables that visualized drayage volume changes caused by different factors and used advanced forecasting models to predict future drayage volume.

We hypothesize that there are several macroeconomic factors that affect the drayage volume, such as the University of Michigan's index of consumer sentiment, inventories to sales ratio, unemployment rate, and gas prices. To understand how these factors correlate with the drayage volume, we first consulted with key business intelligence leaders of our sponsor company and reviewed the data that we collected from external and internal sources. Second, we conducted descriptive analysis, data visualization, and exploratory data analysis to further understand the relationship between the drayage volume and different factors.

After the correlations had been determined, we developed a predictive model to forecast drayage volume and ran multiple scenarios to understand the predictions of the model. After the predictive model is in place, the prediction can help our sponsor company make the most efficient and economical decisions on allocating the right drayage volume capacity to shippers and carriers at the right time under different scenarios.

2 Literature Review

To understand the relationship between drayage volume and various factors, we investigated how macroeconomic factors affected the container volume at each port due to the high correlation between drayage volume and container volume. Our sponsor company only had 3 years of historical drayage data which is not a suitable proxy for the overall U.S. drayage volume due to our sponsor company's rapid business growth. Therefore, we used the loaded and imported container volume as a proxy for the overall U.S. drayage volume. We reviewed the literature for macroeconomic factors that impact the volume of import and export containers, and potential methodologies to predict the volume of containers. In addition, we conducted interviews with supply chain professionals to grasp the impact of macroeconomic factors (e.g., trade war, consumer spending, etc,.) and uncontrollable factors that influence container volume at different ports. These insights will provide the qualitative context to help understand the limitation of our forecast model.

2.1 Macroeconomic Factors

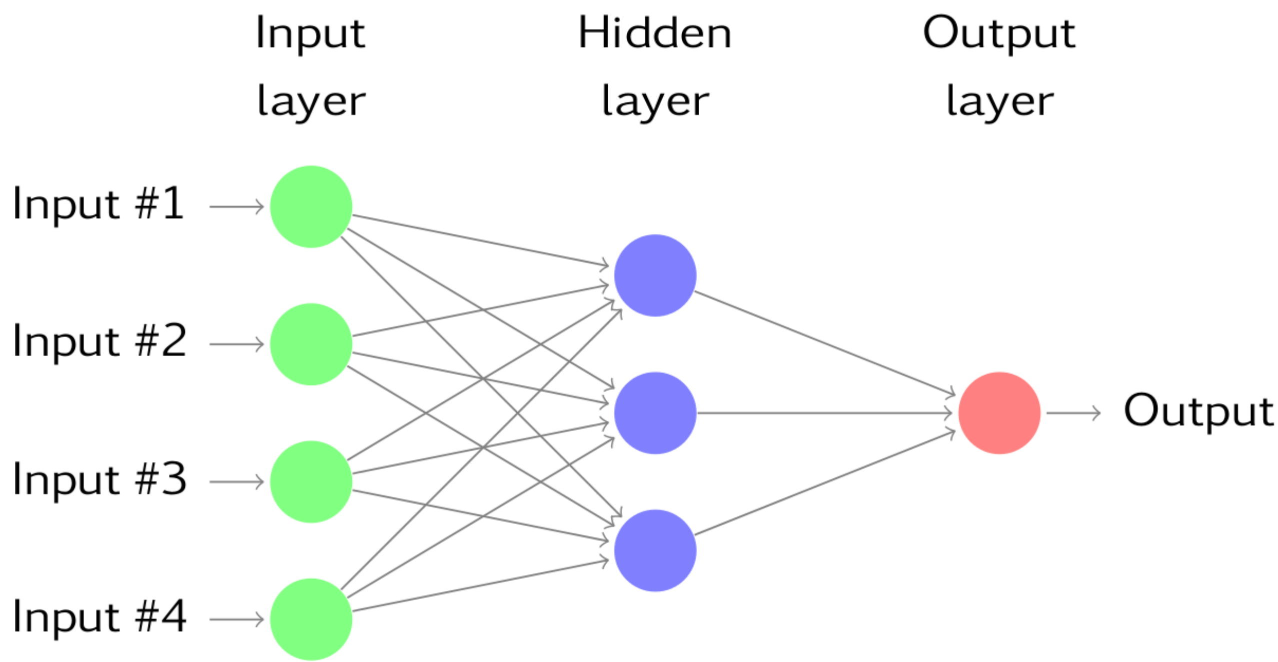
Macroeconomic factors, such as Gross Domestic Product (GDP) and Consumer Price Index (CPI), are often used to evaluate the economic status of a country. In recent years, these factors have been used to forecast many industrial activities such as importing and exporting. Several studies explored how different macroeconomic factors could affect import and export volumes. In one of the studies, Gosasang et al. (2011) used domestic GDP, global GDP, exchange rates, population, inflation rates, interest rates, and fuel prices as independent variables to predict the volume of containers at a Bangkok port. The study suggested a strong relationship between these macroeconomic factors and the volume of import/export containers at the port. In another study, Chou et al. (2008) used population, industrial production index, Gross National Product (GNP), GNP per capita, wholesale GDP, agriculture GDP, industrial GDP, and service GDP as factors in a modified regression model to forecast the volume of import containers in Taiwan. Tyler (1981) examined the empirical link between economic growth and export expansion in emerging nations. Bivariate tests using data from 55 middle-income developing nations for the years 1960–1977 showed substantial positive relationships between economic growth indicators such as GDP and a number of economic variables, such as the expansion of manufacturing output, investment, total exports, and manufacturing exports. By investigating the relevance of these macroeconomic factors through research and supply chain professional interviews, we would identify which can be used in our predictive model to forecast imported container volume in U.S. ports.

2.2 Predictive Methods

To predict the import and loaded container volumes considering various exogenous factors, researchers have used several different predictive methods. Here we discuss four commonly used methods: Multilayer Perceptron (MLP), Modified Regression Model, Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors (SARIMAX), and Vector AutoRegression Model (VAR).

MLP is a common type of artificial neural network that is widely used for supervised prediction. As Figure 1 shows, it takes a linear combination of input signals and transforms them through activation functions to outputs (Gosasang et al., 2011). The input layer of a neural network comprises neurons that represent the input features. In the hidden layer, each neuron takes the values from the previous layer, multiplies them by specific weights, adds them together, and then applies a non-linear activation function. The output layer receives the values from the final hidden layer and transforms them into the desired output values (Pedregosa et al., 2011). Using this method could utilize the input data efficiently with one or two hidden layers and generate valid output for decision-makers. For example, this method generated fewer forecast errors than the traditional linear regression model to forecast container throughput at Bangkok Port (Gosasang et al., 2011).

Figure 1: A Neural Network With Four Inputs and One Hidden Layer With Three Hidden Neurons



Note. Adapted from Neural network models | Forecasting: Principles and Practice (2nd ed)-11.3

The second method, a modified regression model, considers non-stationary contribution coefficients produced by macroeconomic factors to forecast data more accurately than traditional regression models (Chou et al., 2008). Non-stationary contribution coefficients are estimated based on the assumption that the relationship between the macroeconomic factors and the dependent variable is not constant over time, but changes with the underlying economic conditions. This type of modeling is particularly useful when dealing with time series data that exhibit non-stationary behavior, meaning that the statistical properties of the data change over time. According to Chou et al. (2008), some researchers have traditionally predicted container volumes using classic regression techniques. However, those researchers did not take into account the non-stationary contribution coefficient caused by macroeconomic factors. So, their forecasts were biased positively. In order to decrease errors caused by the non-stationary contribution coefficient and, more importantly, to give decision-makers a forecast with a higher level of accuracy, a modified regression model is proposed as a method for predicting the volume of import containers (Chou et al., 2008).

The SARIMAX model is a widely used time series forecasting method when it's necessary to consider external variables in analyses. This model combines the autoregressive, differencing, and moving average processes to model non-stationary time series and uses past values to predict future values. It also considers seasonal patterns of the data and external variables to capture the impacts on time series (Peixeiro, 2022). As our sponsor company wants to understand how different macroeconomic factors could affect the drayage volume, the SARIMAX model could be useful in this field where seasonality and exogenous variables are important factors.

Lastly, the Vector Autoregression (VAR) model is useful for describing the behavior of time series for forecasting and analysis of multivariate time series (Zivot & Wang, 2006). Also, Zivot et al. (2006) mentioned that the VAR can generate insights into the causal impacts of the response of the dependent variable to an unexpected shock in another variable. Specifically, the impulse response functions and forecast error variance decompositions will help with structural inference and policy analysis. In practice, Gao et al. (2016) utilized the VAR model to predict tourism destination arrivals. In their research, they incorporated several exogenous variables in the model, namely web search queries, weather, temperature, daily tickets, public holidays, and weekends. In addition, Sokoloff & Zhang (2020) used the autoregressive integrated moving average (ARIMA) and VAR models to forecast US truckload dry van spot rate.

It was noted that they used ARIMA for short-term forecast due to its accuracy on short-term prediction as opposed to a longer-term forecast horizon. The VAR was used due to great forecast accuracy and effectiveness with multivariate time series forecasting. By incorporating the key exogenous variables in the trucking industry, their models achieved an average MAPE below 7% which allowed the sponsor company to employ their playbook for risk mitigation.

Based on our review of different methodologies, both VAR and SARIMAX could be used for forecasting in our study. However, SARIMAX was selected due to the following reasons:

1. SARIMAX is built for univariate time series analysis rather than how multiple time series relate to each other. It aligns with our objective to incorporate exogenous variables in the forecast model and understand how they affect imported container volume.
2. Model Complexity and Interpretability: SARIMAX is easier to interpret in terms of evaluating the impact of exogenous variables on our time series. In contrast, VAR focuses on analyzing how multiple time series variables are interrelated. It takes more computational power and is harder to interpret the effect of the exogenous variables.
3. Our sponsor company was interested in a 3-month forecast horizon for setting near-term priorities, resource planning, and financial forecasting.

Hence, SARIMAX aligns with our project scope and our sponsor company can leverage a 3-month rolling forecast report to update throughout the year.

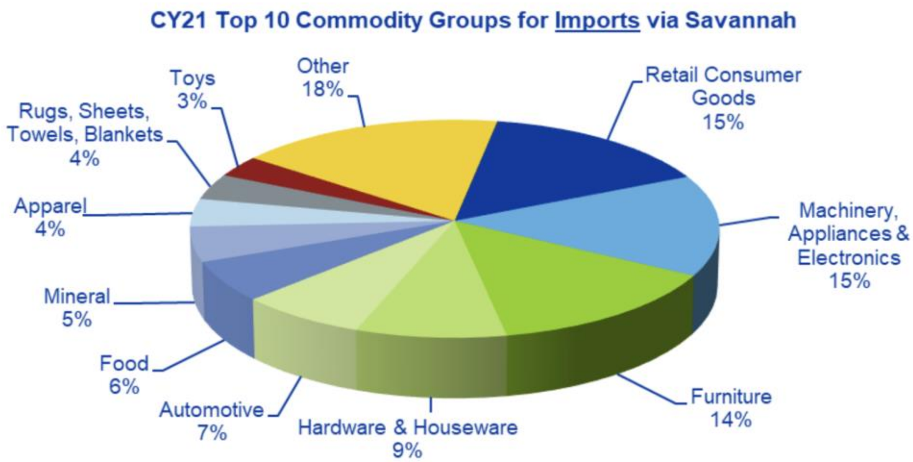
3 Data and Methodology

This chapter describes the data and methodology we used. We interviewed three supply chain professionals to understand what factors may affect container volume and the macroeconomic indicators they monitor and use for forecasting (details are shared in Section 5.1). After consultation, we also reviewed research reports and articles from different resources to gain additional qualitative insights, such as the *Wall Street Journal*, *Journal of Commerce*, and *FTR Transportation Intelligence*.

3.1 Macroeconomic Indicators Selection

Combining the insights from the interviews, research reports, and articles, we believed the U.S. imported container volume could be highly correlated with the overall economy and consumer spending. To select the macroeconomic indicators for modeling purposes, we referred to the volume of top commodity groups for imports at different ports, including the Port of Savannah, Port of Long Beach, Port of Houston, and Port of New York and New Jersey. For example, Figure 2 outlines the top commodity groups for imports via the Port of Savannah. As for the port of Long Beach, its top 5 imports are crude oil, electronics, plastics, furniture, and clothing. The majority of their imports are consumer goods and housing related. Therefore, we selected a number of potential macroeconomic indicators that reflected U.S. consumer spending and incorporated them into the SARIMAX model to validate our hypothesis. For instance, retailers make importing decisions mainly based on sales and inventory level, hence the Retailers Inventories and Advanced Retail Sales would be the best indicators for fitting the forecast model. To narrow down the consumer and business leading indicators, we reviewed the imported container volume by top commodities at different ports. Table 1 outlines all the macroeconomic indicators we selected for fitting the model.

Figure 2: CY 21 Top 10 Commodity Groups for Imports via Savannah



Note. Adapted from "Five Year History for Top 10 Commodity Groups for Imports via Savannah (Calendar Year)" by Georgia Ports. (https://gaports.com/wp-content/uploads/2022/05/CY21-Top-10-Commodity-Groups-Imports.pdf?1682972802)

Table 1: Data Dictionary of Macroeconomic Indicators/Exogenous Variables Used

Macroeconomic Indicator (with abbreviation)	**Definition**	**Units**	**Source**
Retailers Inventories	Inventory holding by retailers	Million of Dollars	U.S. Census Bureau
Advance Retail Sales: Retail Trade (Retail Sales)	Estimate of monthly sales for companies in the retail trade and food services sectors	Million of Dollars	U.S. Census Bureau
New Privately-Owned Housing Units Started: Total Units (New Housing Units Built)	Estimates of privately-owned housing units starts	Thousands of Units	U.S. Census Bureau and U.S. Department of Housing and Urban Development
University of Michigan: Consumer Sentiment	A monthly survey of how consumers feel about the economy, personal finances, business conditions, and buying conditions	Index	University of Michigan
Producer Price Index by Commodity: Fuels and Related Products and Power: Natural Gas (PPI: Natural Gas)	Measure of the average change over time in the selling prices of natural gas	Index	U.S. Bureau of Labor Statistics
Total Vehicle Sales	Monthly auto and trucks sales	Million of Units	U.S. Bureau of Economic Analysis
All Employees, Total Nonfarm	A measure of the number of U.S. workers in the economy	Thousands of Persons	U.S. Bureau of Labor Statistics
Unemployment Rate	The number of unemployed as a percentage of the labor force	Percent	U.S. Bureau of Labor Statistics
Consumer Price Index for All Urban Consumers: Fuel Oil and Other Fuels in U.S. City Average (CPI: Fuel)	Consumer Price Index for All Urban Consumers: Fuel Oil and Other Fuels in U.S. City Average	Index	U.S. Bureau of Labor Statistics

Note. Adapted from the Federal Reserve Economic Data. (https://fred.stlouisfed.org/)

3.2 SARIMAX Model

Before we incorporated macroeconomic indicators into our model, we utilized seasonal naïve forecasting to obtain a baseline forecast for imported container volume. Seasonal Naïve forecasting simply uses the last observation from the same month in the previous year. We would compare the SARIMAX forecast to the Seasonal Naïve forecast to evaluate the effectiveness. Then, we developed the SARIMAX model through the following steps:

3.2.1 Data Collection

We used 13 years of monthly loaded and imported twenty-foot equivalent unit (TEU) container volume data (2010 - 2022) from the official websites of the ports of Savannah, Long Beach, Houston, and New York and New Jersey as our dependent variables. We chose these four ports due to their large imported container volume and the majority of our sponsor company's drayage service sales were from these ports. For macroeconomic indicators (exogenous variables), we used the Federal Reserve Economic Data (FRED) that is maintained by the Research Division of the Federal Reserve Bank of St. Louis.

3.2.2 Incorporating Lagged Exogenous Variables

Having all the monthly data for potential macroeconomic indicators listed in Table 3.1, we investigated their relevance with imported container volumes. Because our sponsor company preferred a three-month forecast for near-term capacity and financial planning and we cannot use future indicators to forecast, a minimum of a three-month lag is needed to avoid data leakage when incorporating macroeconomic indicators into the model. To identify the relevance between imported container volumes and lagged macroeconomic indicators at each port, we used the correlation coefficient matrix and selected those lagged macroeconomic indicators that had high correlation coefficients. Then, we created different combinations of those macroeconomic indicators and incorporated them into our model.

3.2.3 Training and Testing

To test our model's performance, we split the 13-year data into 10 different training and testing set combinations. As shown in Table 2, all training sets started in January 2010 and all testing sets were in a three-month period. A three-month rolling period in testing sets allowed us to better evaluate the model's accuracy in forecasting three months ahead.

Table 2: Training and Testing Split

Training Set		Testing Set	
Start Date	End Date	Start Date	End Date
1/2010	12/2021	1/2022	3/2022
1/2010	1/2022	2/2022	4/2022
1/2010	2/2022	3/2022	5/2022
1/2010	3/2022	4/2022	6/2022
1/2010	4/2022	5/2022	7/2022
1/2010	5/2022	6/2022	8/2022
1/2010	6/2022	7/2022	9/2022
1/2010	7/2022	8/2022	10/2022
1/2010	8/2022	9/2022	11/2022
1/2010	9/2022	10/2022	12/2022

3.2.4 Fitting the Model

The SARIMAX model is expressed as SARIMAX(p,d,q)(P,D,Q)m + X. It has 7 parameters: order of autoregressive term (p), degree of differencing (d), order of moving average term (q), seasonal order of autoregressive term (P), seasonal degree of differencing (D), seasonal order of moving average term (Q), and seasonal period (m). Besides the key parameters, X represents the additional term for exogenous variables. By fitting data into our model using the Python package, it finds the optimized (p, d, q)(P, D, Q) with the lowest AIC (Akaike Information Criterion). AIC is a statistical measure that is commonly used in time series analysis. It takes into account the goodness of fit of the model as well as the complexity of the model, with a lower AIC value indicating a better balance between fit and complexity.

3.2.5 Model Evaluation

After fitting the training sets with python, we made predictions on the testing sets with different combinations of selected macroeconomic indicators and compared the predictions with actual imported container volumes. Then, we evaluated the model forecast accuracy through Mean Absolute Percentage Error (MAPE) for each testing set. Once we had all the results, we selected the combination of macroeconomic indicators that had the lowest MAPE for each port.

Forecast Value Added (FVA) is a performance metric that is used to evaluate the effectiveness of forecasting. In this project, we used it to measure the accuracy of our forecast model relative to the baseline forecast model using seasonal naïve forecast. For example, if the MAPE was 10% in our SARIMAX model, where a seasonal naïve forecast achieved a MAPE of 3%. We could say that our forecast model did not add value since the difference of their MAPEs divided by the MAPE of seasonal naïve forecast is (3% - 10%) / 3% = -233.3%. A positive percentage increase represents how much value our forecast model could add compared to the naïve forecast, and vice versa. Once the MAPEs were generated by the SARIMAX model for each testing set, we compared them with seasonal naïve forecast results to get the FVA.

4 Results

Our Project used SARIMAX to forecast the imported container volume at different ports incorporating relevant macroeconomic indicators. We selected four major ports in the U.S. and conducted our analysis. Each port's dataset contains 156 line records and we used 9 macroeconomic indicators to test different combinations to fit the SARIMAX model.

4.1 Baseline Model Metrics

We used the seasonal naïve model to forecast the loaded and imported container volume for each port starting from January 2022 with a three-month rolling period and calculated the MAPEs as baseline metrics. Table 3 depicts the seasonal naïve model's accuracy for each port. The model performed differently at each port since imported container volumes were affected not only by commodity groups but also by macroeconomic indicators. In addition, the seasonal naïve model could not capture the trend of the dataset, so the average MAPE was relatively high at each port.

Table 3: Baseline Model Results (Seasonal Naïve) for Jan to Dec 2022

	Seasonal Naive - MAPE										
Ports	Jan-Mar	Feb-Apr	Mar-May	Apr-Jun	May-Jul	Jun-Aug	Jul-Sep	Aug-Oct	Sep-Nov	Oct-Dec	**Average**
Savannah	13.1%	12.1%	9.8%	6.1%	7.9%	11.1%	12.4%	9.8%	6.9%	6.5%	**9.6%**
Long Beach	5.1%	5.7%	4.9%	8.1%	5.9%	7.3%	5.3%	15.0%	26.2%	39.7%	**12.3%**
Houston	20.6%	19.9%	16.4%	16.3%	14.0%	12.4%	16.5%	17.2%	15.9%	10.9%	**16.0%**
New York and New Jersey	10.4%	13.0%	10.9%	11.2%	7.2%	7.1%	6.5%	7.1%	8.0%	14.2%	**9.6%**

4.2 Correlation between Port Volume and Lagged Macroeconomic Indicators

With the potential macroeconomic indicators, we used the correlation matrix to evaluate the relevance of port container volumes to different lagged macroeconomic indicators. Table 4 shows the results of the correlation coefficients for each port. Based on the absolute value of the correlation coefficients, we selected those macroeconomic indicators with high correlation coefficients, which are Advanced Retail Sales, New Housing Units Built, Total Vehicle Sales, Unemployment Rate, Total Nonfarm, and CPI: Fuel, to incorporate into our model. As Chapter 3 mentioned, these indicators are all in a three-month lag.

Table 4: Correlation Coefficients matrix *for Different Ports and Macroeconomic Indicators*

Macroeconomic Indicators	Correlation Coefficients between the Macroeconomic Indicators (3-month lag)							
Advanced Retail Sales								
New Housing Units Built	91.8							
Total Vehicle Sales	25	47.9						
Total Nonfarm	79.3	85.9	59.7					
Unemployment Rate	-60.5	-70.7	-71.1	-92.5				
CPI: Fuel	26.6	0.8	-29.9	2.2	-6			
PPI: Natural Gas	8.4	-16.4	-49.1	-17	10.6	73		
Consumer Sentiment	-2.8	25.5	78.3	46.4	-54.9	-58.8	-65.1	
Retailers Inventory	83.2	88	54.9	95.5	-81.4	3	-17.4	38
	Advanced Retail Sales	New Housing Units Built	Total Vehicle Sales	Total Nonfarm	Unemployment Rate	CPI: Fuel	PPI: Natural Gas	Consumer Sentiment

Macroeconomic Indicators	Loaded + Import TEUs by Ports vs. Macroeconomic Indicators (3-month lag)			
Advanced Retail Sales	92.4	65.1	96.3	91
New Housing Units Built	88.4	68	88.5	85
Total Vehicle Sales	25.8	22.7	20.7	18.7
Total Nonfarm	76.2	47.9	77.5	68.2
Unemployment Rate	-53.2	-31	-55.6	-45.9
CPI: Fuel	3.3	-7.4	18.3	10.7
PPI: Natural Gas	-8.8	-17.2	3.5	-4.1
Consumer Sentiment	10.2	13.5	0.9	0.7
Retailers Inventory	82.2	54.4	83.1	74.5
Ports	Savannah	Long Beach	Houston	New York and New Jersey

4.3 Model Accuracy

Having selected the relevant macroeconomic indicators, we tested the combinations of those macroeconomic indicators to identify which one would generate the lowest MAPE using SARIMAX to forecast 3-month rolling import container volumes at each port. Table 5 depicts the finalized combinations of macroeconomic indicators. These indicators are highly correlated with commodity groups at each port and overall economic conditions. In addition, MAPEs that are generated by the SARIMAX model are shown in Table 6. The average MAPE for each port was below 10% except for the Port of Long Beach due to the significant volume drops in the fall of 2022. We hypothesized that there might be other non-macroeconomic factors that affected the imported container volume, which has yet to be included in the existing model, thus resulting in the model's inability to fully capture the extent of their impact.

Table 5: Macroeconomic Indicators Used in Different Ports

	Macroeconomic Indicators					
Ports	New Housing Units Built	Retail Sales	Vehicle Sales	Nonfarm Payroll	Unemployment Rate	CPI: Fuel
Savannah	X	X				
Long Beach	X		X			X
Houston	X	X	X			
New York and New Jersey		X	X	X	X	X

Table 6: SARIMAX 3-month Rolling Forecast MAPE

	3-month Rolling Forecast (SARIMAX) - MAPE										
Ports	Jan-Mar	Feb-Apr	Mar-May	Apr-Jun	May-Jul	Jun-Aug	Jul-Sep	Aug-Oct	Sep-Nov	Oct-Dec	**Average**
Savannah	6.1%	6.3%	6.6%	7.5%	4.7%	3.3%	10.8%	12.0%	23.1%	11.1%	**9.2%**
Long Beach	13.1%	8.4%	6.8%	1.8%	5.1%	12.0%	16.7%	13.9%	27.6%	31.9%	**13.7%**
Houston	6.2%	5.3%	5.2%	3.4%	2.1%	3.5%	4.7%	5.9%	4.3%	16.2%	**5.7%**
New York and New Jersey	5.5%	6.9%	11.0%	3.3%	3.5%	4.2%	6.8%	4.0%	7.5%	17.9%	**7.1%**

4.4 Forecast Value Added

By comparing the MAPEs using SARIMAX with ones using seasonal naïve, we calculated the FVA, as shown in Table 7. The model generated an average positive FVA at each port except for the Port of Long Beach. In addition, FVAs that are larger than zero indicate the forecast is better than the forecast using the seasonal naïve method.

After research, in addition to economic changes and uncertainty, we believe that the labor negotiation issue at the Port of Long Beach had a significant impact on the port operation and shippers shifted volume elsewhere to avoid potential disruption. The Port of Los Angeles Executive Director Gene Seroka mentioned a few factors that caused a major volume decline starting in 2022, including a drop in demand, high inventory levels, longer factory closures during the Lunar New Year, and the ongoing longshore labor negotiations (Miller, 2023).

For the Port of Savannah, the supply chain operations were severely impacted by Hurricane Ian in September 2022, the 5th-strongest hurricane on record in the United States. In this case, our forecast model was unable to capture the unexpected container volume decline due to natural disasters. There are some other limitations in our model, and we will discuss them in Chapter 5.

Table 7: Forecast Value Added Using SARIMAX

	Forecast Value Added										
Ports	Jan-Mar	Feb-Apr	Mar-May	Apr-Jun	May-Jul	Jun-Aug	Jul-Sep	Aug-Oct	Sep-Nov	Oct-Dec	**Average**
Savannah	53.4%	47.9%	32.7%	-23.0%	40.5%	70.3%	12.9%	-22.4%	-234.8%	-70.8%	**4.4%**
Long Beach	-156.9%	-47.4%	-38.8%	77.8%	13.6%	-64.4%	-215.1%	7.3%	-5.3%	19.6%	**-11.4%**
Houston	70.0%	73.6%	68.3%	79.4%	84.8%	72.2%	71.3%	65.5%	73.0%	-48.3%	**64.6%**
New York and New Jersey	47.4%	47.2%	-0.8%	70.2%	51.9%	41.0%	-4.8%	43.9%	6.4%	-26.1%	**26.2%**

5 Discussion

The following chapter will discuss our insights regarding how various factors affect container import volume and the limitations of our SARIMAX model, based on research reports, journal articles, and feedback from supply chain professional interviews.

5.1 Supply Chain Professional Interviews

The interviews were conducted in December 2022 with Taylor Worley, the marketing research analyst at the Georgia Ports Authority; Jackson Tsai, the Vice President of the China Shippers' Association and an official at the Ministry of Commerce of the People's Republic of China; Toby Gooley, the former editor of Supply Chain Quarterly and senior editor of DC Velocity. Our objective was to incorporate a qualitative approach into our project, gain insights into what factors may affect U.S. container imports, and learn about what macroeconomic indicators they closely monitor.

5.2 Respondent Summary

The recurring theme from the respondents is that U.S. container imports are highly correlated with the overall economy and consumer spending. Retailers often make importing decisions based on the business environment, trade policy, growth opportunities, tariffs, and currency exchange rates. For the Port of Savannah, Taylor Worley uses retailer sales, inventory level, and housing market indicators for forecasting because much of their imports are related to consumer goods and housing (furniture). In addition, Jackson Tsai believes the U.S. container import volume decline in 2022 is mainly driven by the following factors:

1. The skyrocketing inflation rate and commodity prices
2. Rising interest rate
3. Economic uncertainty and weakened consumer demand
4. Excess inventory

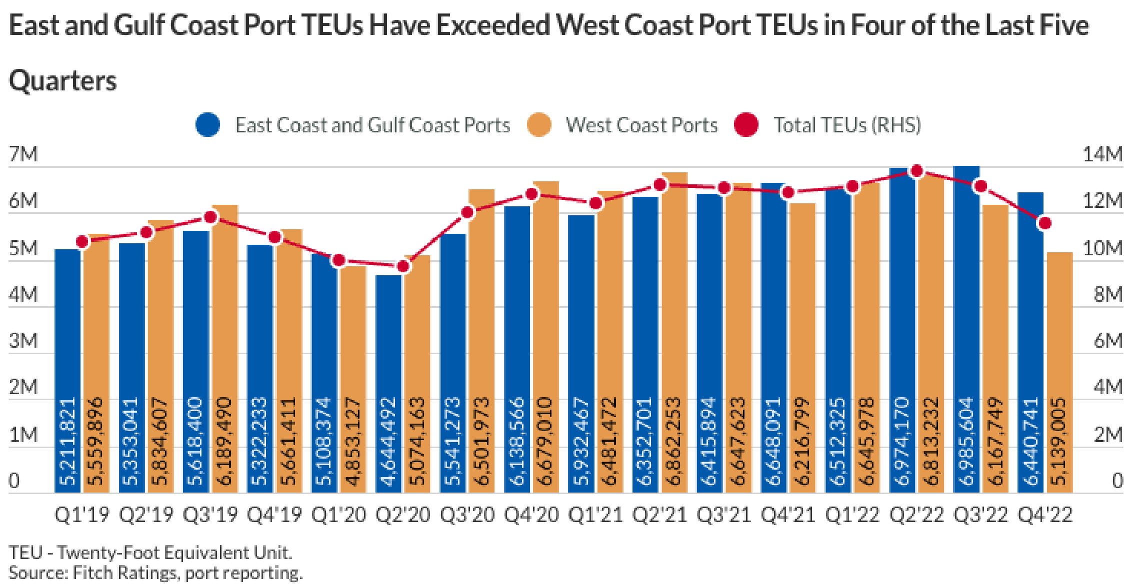
The respondents provided us with the qualitative context of the economic environment and uncontrollable factors (ex. the zero-COVID policy) that impact U.S. imports. Their insights provided us with a clear direction on macroeconomic indicators selection so we can incorporate them into our forecast model as exogenous variables.

5.3 The Impact of Economic Events

Changes in trade policy can have major impacts on import container volume. For instance, the Trump Administration decided to raise tariffs on many Chinese goods from 10% to 25% by the end of 2018. Gooley (2019) described the importers' reactions as follows: "Some importers went into overdrive, pushing their suppliers to ship as much merchandise as possible into the U.S. before the end of 2018. Ocean carriers put on extra sailings, and major seaports across the country saw record-high levels of imports in November, December, and into January." The bullwhip effect of the trade policy led to operational delays and bottlenecks across the supply chain and inaccurate forecasting for carriers and freight brokers.

On the other hand, according to Fitch Wire (2023) and the insights from supply chain professional interviews, many shippers have been shipping to the Gulf Coast and East Coast ports from Asia in anticipation of labor contract negotiations and potential strikes at the port of Long Beach. Retailers cut back on their imports due to shifts in consumer spending levels, inflation, interest rates, and excess inventory. Hence, they led to a significant decline in the port of Long Beach and a volume shift to the East and Gulf Coast ports in the last few quarters. Figure 3 shows the TEU volume of the East and Gulf Coast ports and West Coast ports.

Figure 3: East and Gulf Coast Ports vs. West Coast Ports (TEUs)



Note. Adapted from "West Coast Port Volumes Lowest in Over a Decade; East, Gulf Coasts Gain", 2023, Fitch Ratings (https://www.fitchratings.com/research/infrastructure-project-finance/west-coast-port-volumes-lowest-in-over-decade-east-gulf-coasts-gain-22-03-2023)

Meanwhile, port expansion also plays an important role in a container volume increase in the East and Gulf Coast ports. For instance, Georgia Ports Authority (2022) shared the ongoing initiatives in the 2022 State of the Port: "Projects now under way will add 1.7 million TEUs of annual capacity in four months. GPA's Peak Capacity project has already added 400,000 TEUs in container handling space to the Garden City Terminal and will make room for another 820,000 TEUs by June…Another 17 million square feet are now under construction, lifting the market beyond 100 million square feet to better accommodate heightened cargo volumes.” We suggest that, in addition to utilizing our SARIMAX model, our sponsor company should closely monitor the press releases by port authorities and local economic development agencies to identify information about planned business expansions.

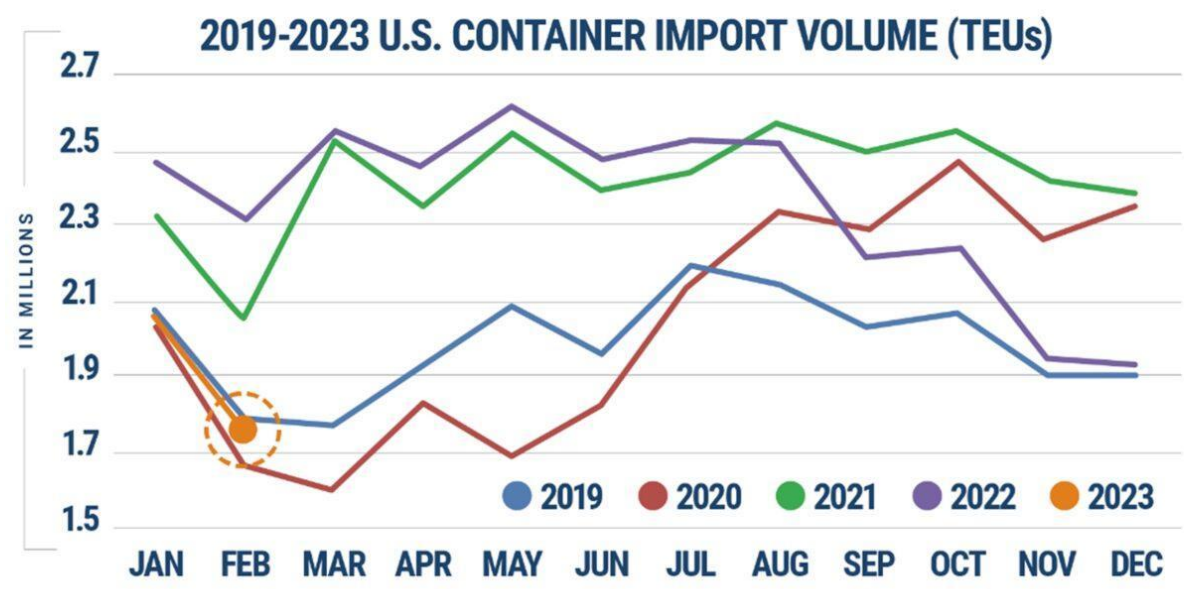
Considering all these, the U.S. import is closely tied to economic events that may not be timely reflected or captured in macroeconomic indicators. Geopolitics assessment is not an easy task, our sponsor company should consider leveraging a political risk consultancy to understand the impact of politics and trade policy on risks and opportunities. These insights will provide a holistic and qualitative perspective for its long-term business planning and import container volume forecast.

5.4 The Impact of Uncontrollable Factors

Natural disasters can lead to major supply chain disruptions, but it is nearly impossible to predict exactly when and where they will happen. Hurricane Ian, the 5th-strongest hurricane on record in the United States, caused the closure of major ports, railroads, and facilities in 2022. The Florida ports were either closed or implemented restrictions and required Coast Guard’s authorization to resume operations. The local governments, ports, and carriers were prepared for the arrival of Hurricane Ian, but it still brought significant disruption to supply chain operations (Murray, & Saraiva, 2022). For instance, the storm led to a big drop in the port of Savannah’s import container volume in September 2022: A 10% and 28% drop compared to the previous month and September 2021 levels, respectively.

In addition to natural disasters, COVID-19 was another unpredictable factor that had a significant impact on import container volume. Figure 4 depicts the U.S. Container Import Volume (TEUs) between 2019 and 2023. The COVID-19 pandemic caused huge volatility in import volume after retailers' inventories dropped to near-historic lows and they paid a premium on shipping to get products on shelves as soon as possible. In our interview with Jackson Tsai, he shared that retailers cut back on imports also due to the unpredictable lead time in manufacturing and logistics under the Chinese government's zero-COVID policy. Because of the COVID-19 local restrictions and facility closures, the policy led to supply disruption and a low manufacturing order fulfillment rate.

Figure 4: 2019 - 2023 U.S. Container Import Volume (TEUs)

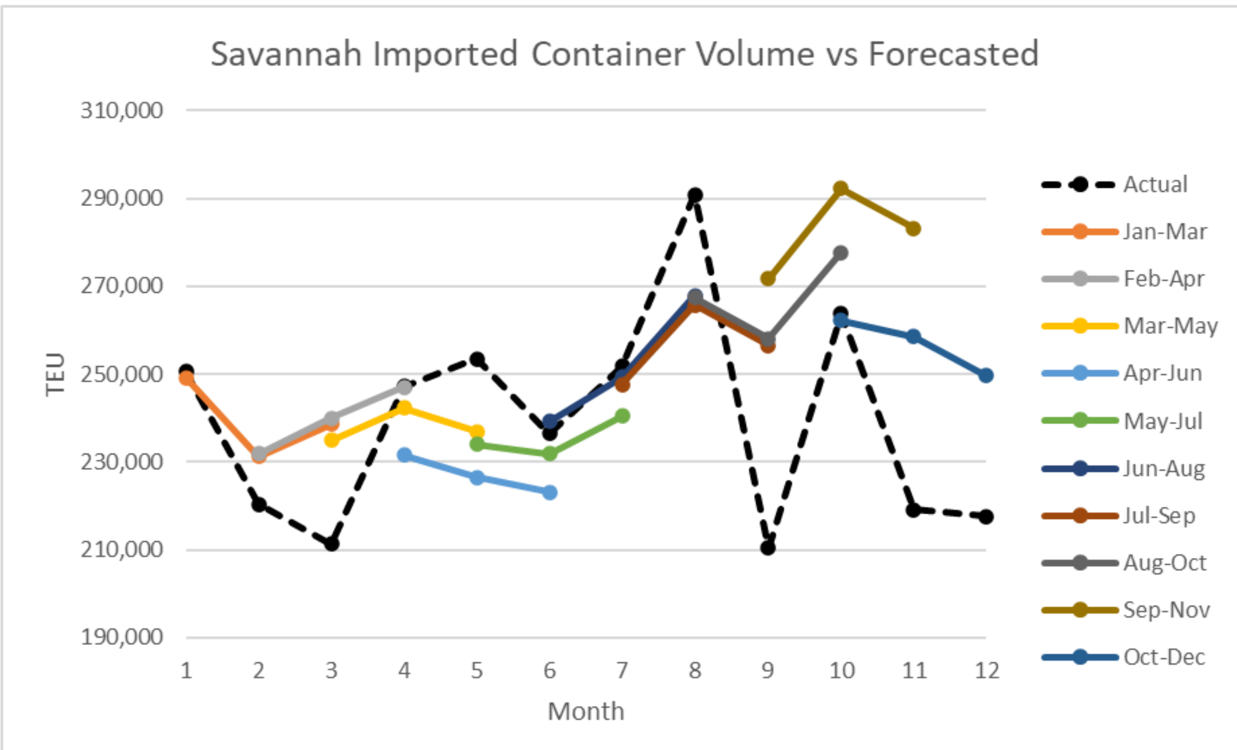


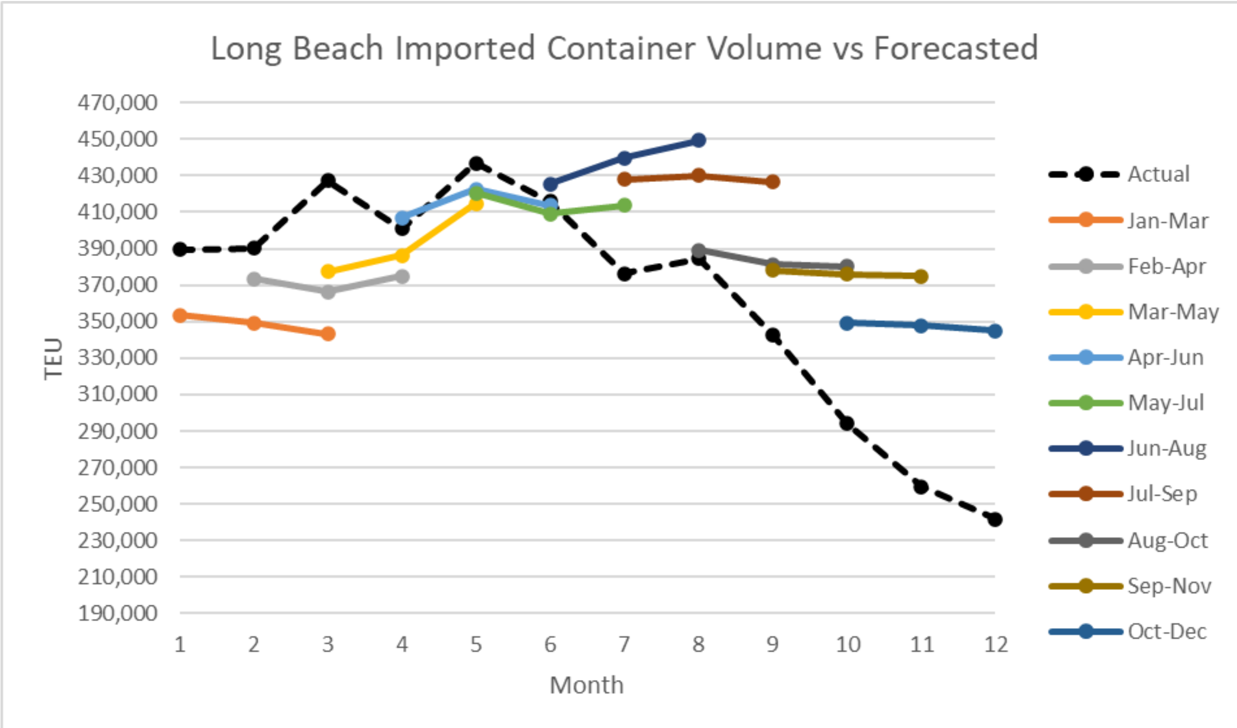
Note. Adapted from "Imports sink again as wholesale inventories remain bloated" by Greg Miller, 2023, Freight Waves. (https://www.freightwaves.com/news/imports-sink-again-as-wholesale-inventories-remain-bloated)

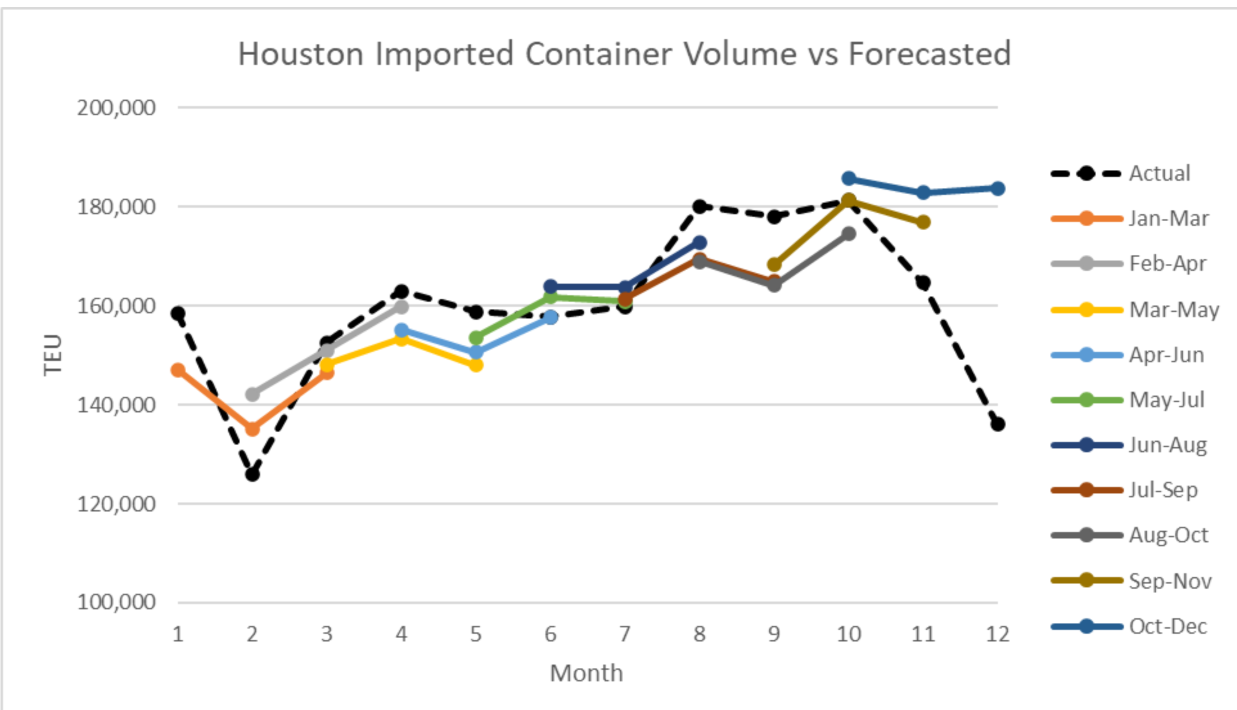
5.5 Limitations and Recommendations

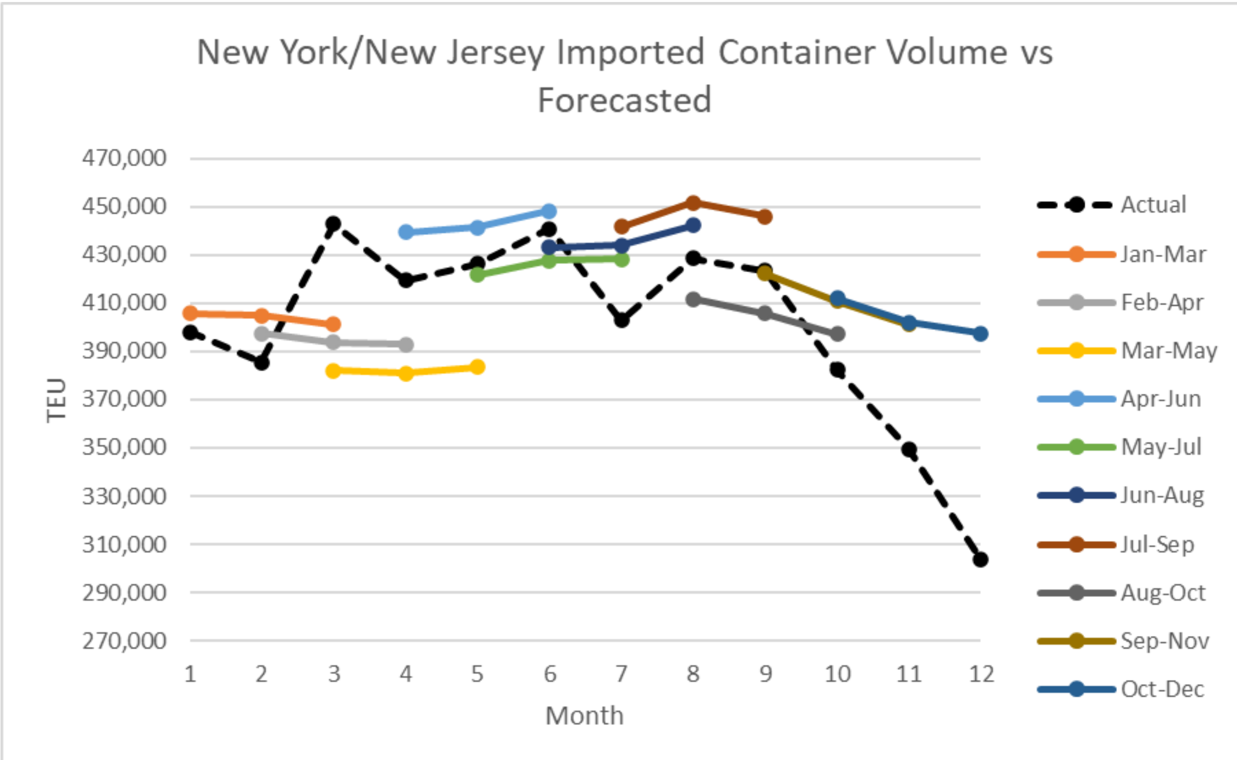
The uncertainty of the COVID-19 pandemic and natural disasters are uncontrollable factors that cannot be incorporated into our forecast model. Figure 5 shows the plots for the 3-month rolling forecast and actual volume. As we observed in the case of the Port of Long Beach (labor negotiation), the prediction of the magnitude of economic events presents a challenging task.

Figure 5: 3-Month Rolling Forecast vs Actual Volume Plots




Long Beach Imported Container Volume vs Forecasted
470,000
450,000
430,000
410,000
390,000
370,000
350,000
330,000
310,000
290,000
270,000
250,000
230,000
210,000
190,000
TEU
1
2
3
4
5
6
7
8
9
10
11
12
Month
Actual
Jan-Mar
Feb-Apr
Mar-May
Apr-Jun
May-Jul
Jun-Aug
Jul-Sep
Aug-Oct
Sep-Nov
Oct-Dec


Houston Imported Container Volume vs Forecasted
200,000
180,000
160,000
140,000
120,000
100,000
TEU
1
2
3
4
5
6
7
8
9
10
11
12
Month
Actual
Jan-Mar
Feb-Apr
Mar-May
Apr-Jun
May-Jul
Jun-Aug
Jul-Sep
Aug-Oct
Sep-Nov
Oct-Dec



Considering the limitations and various factors involved, we suggest implementing several initiatives to prepare for these events:

1) Close Communication with Carriers: Regularly communicate with carriers/truckers to understand their capacity and pivot to alternative options if needed.
2) Business Contingency Planning: Develop a contingency plan that can address sudden changes in capacity and customer demand.
3) Stay Up to date: Monitor the latest developments of the event and how it impacts the supply chain operations. By understanding the scale and magnitude, the sponsor company can use this information to set priorities for resource planning and forecasting.

6 Conclusion

As the U.S. import volume becomes more volatile in recent years, our sponsor company is experiencing a harder time predicting the drayage volume and allocating the right drayage volume capacity to different ports. This capstone project incorporated exogenous variables (macroeconomic indicators) into a SARIMAX model to produce near-term drayage volume forecasts and understand the effects of various factors at different ports. We used 13 years of monthly loaded and imported container volume data at 4 major ports as our dependent variables. Our sponsor company's historical drayage data was not used because it only had 3 years of data and was not a suitable proxy for the overall US drayage volume due to our sponsor company's rapid business growth.

The qualitative analysis was performed by reviewing research reports, literature, and articles, and conducting supply chain professional interviews. As demonstrated in this report, the imported container volume was highly correlated with the overall economy and consumer spending. Moreover, the macroeconomic indicators in our model differ by port. For example, the New Housing Units Built and Retail Sales produce a desirable forecast accuracy for the Port of Savannah because much of its imports are housing-related (ex. furniture). It indicated that the top commodity groups at different ports played an important role in the forecast.

In this study, we identified relevant macroeconomic indicators that affected the import container volume at different ports. We studied the impact of economic events and uncontrollable factors that may not be timely reflected in macroeconomic indicators and incorporated them into our SARIMAX model. As discussed in the report, our sponsor company should collect qualitative information from different sources, such as press releases by port authorities and political assessment by a political risk consultancy. Ultimately, our sponsor company can utilize our SARIMAX model to create a 3-month forecast for U.S. imported container volume (a proxy for drayage) at different ports.

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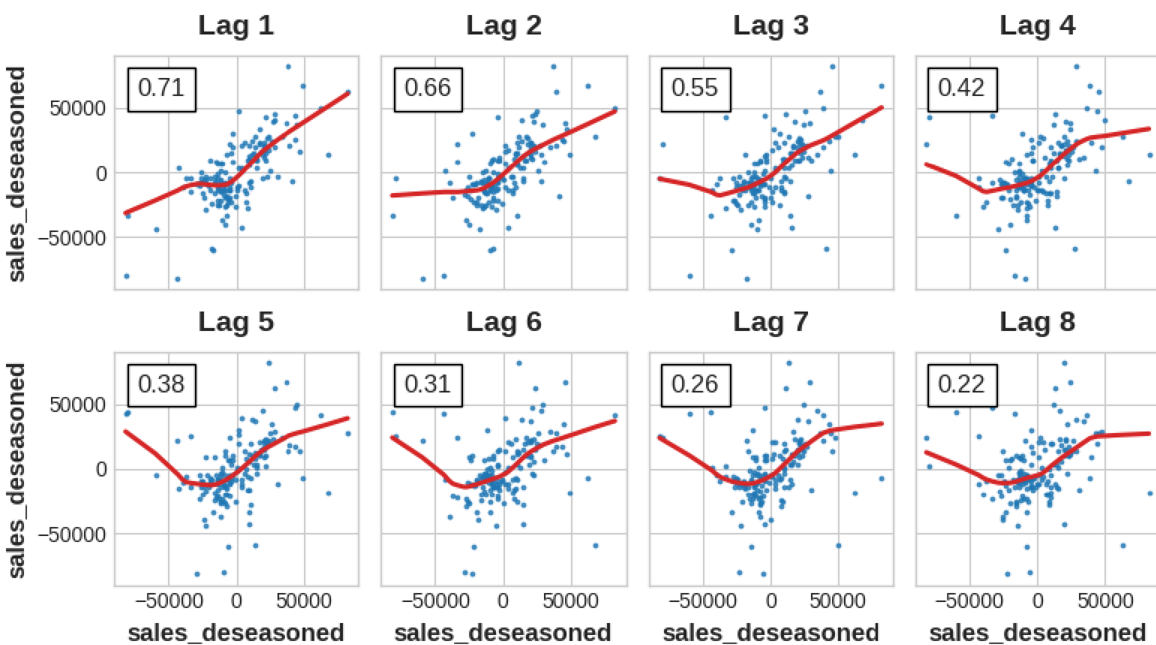
Appendix

Lag Plots of New York and New Jersey:



SARIMAX Summary by Ports

Port of Houston

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                             TEU Vol   No. Observations:                  144
Model:             SARIMAX(0, 1, 1)x(1, 0, 1, 12)   Log Likelihood               -1479.963
Date:                            Wed, 03 May 2023   AIC                           2973.927
Time:                                    12:29:00   BIC                           2994.667
Sample:                                01-01-2010   HQIC                          2982.355
                                     - 12-01-2021
Covariance Type:                              opg
==========================================================================================
                             coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------
Total Vehicle Sales     1234.1787    915.906      1.347      0.178    -560.964    3029.322
Advanced Retail Sales      0.1015      0.073      1.398      0.162      -0.041       0.244
New Housing Units Built   -6.0934      7.596     -0.802      0.422     -20.981       8.794
ma.L1                     -0.6571      0.075     -8.712      0.000      -0.805      -0.509
ar.S.L12                   0.8981      0.124      7.263      0.000       0.656       1.141
ma.S.L12                  -0.6592      0.190     -3.462      0.001      -1.032      -0.286
sigma2                  6.784e+07      0.026   2.58e+09      0.000    6.78e+07    6.78e+07
===================================================================================
Ljung-Box (L1) (Q):                   0.24   Jarque-Bera (JB):                27.43
Prob(Q):                              0.62   Prob(JB):                         0.00
Heteroskedasticity (H):               7.73   Skew:                             0.43
Prob(H) (two-sided):                  0.00   Kurtosis:                         4.97
===================================================================================
```

:

Port of New York and New Jersey:

```
                                       SARIMAX Results
============================================================================================
Dep. Variable:                               TEU Vol   No. Observations:                 144
Model:             SARIMAX(0, 1, 2)x(1, 0, [1], 12)   Log Likelihood              -1624.618
Date:                              Wed, 03 May 2023   AIC                          3269.237
Time:                                      12:34:04   BIC                          3298.865
Sample:                                  01-01-2010   HQIC                         3281.276
                                       - 12-01-2021
Covariance Type:                                opg
=========================================================================================
                           coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Total Vehicle Sales  -1277.4095   3559.859     -0.359      0.720   -8254.606    5699.787
Advanced Retail Sales    0.2822      0.225      1.252      0.211      -0.160       0.724
Total Nonfarm           -9.7606      4.331     -2.254      0.024     -18.249      -1.272
Unemployment Rate    -1.335e+04   8257.247     -1.617      0.106   -2.95e+04    2835.179
CPI: Fuel              136.2027    161.319      0.844      0.398    -179.977     452.382
ma.L1                   -0.0212      0.017     -1.276      0.202      -0.054       0.011
ma.L2                    0.0221      0.042      0.529      0.597      -0.060       0.104
ar.S.L12                 0.9846      0.193      5.113      0.000       0.607       1.362
ma.S.L12                -0.9759      0.220     -4.440      0.000      -1.407      -0.545
sigma2                3.633e+08      0.127   2.86e+09      0.000    3.63e+08    3.63e+08
===================================================================================
Ljung-Box (L1) (Q):                  25.48   Jarque-Bera (JB):                 1.57
Prob(Q):                              0.00   Prob(JB):                         0.46
Heteroskedasticity (H):               2.11   Skew:                            -0.05
Prob(H) (two-sided):                  0.01   Kurtosis:                         2.50
===================================================================================
```

Port of Savannah

```
                                    SARIMAX Results
==========================================================================================
Dep. Variable:                             TEU Vol   No. Observations:                 144
Model:             SARIMAX(2, 1, 2)x(1, 0, [1], 12)   Log Likelihood               -1547.279
Date:                             Wed, 03 May 2023   AIC                           3112.559
Time:                                     02:00:10   BIC                           3139.224
Sample:                                 01-01-2010   HQIC                          3123.394
                                      - 12-01-2021
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
RSXFS_Lag      0.1810      0.094      1.922      0.055      -0.004       0.366
HOUST_Lag    -18.3304     15.665     -1.170      0.242     -49.033      12.372
ar.L1         -1.1441      0.255     -4.490      0.000      -1.643      -0.645
ar.L2         -0.2584      0.242     -1.069      0.285      -0.732       0.215
ma.L1          0.5977      0.246      2.432      0.015       0.116       1.079
ma.L2         -0.3673      0.241     -1.521      0.128      -0.841       0.106
ar.S.L12       0.9116      0.137      6.631      0.000       0.642       1.181
ma.S.L12      -0.6857      0.235     -2.923      0.003      -1.145      -0.226
sigma2      1.988e+08   3.22e-06   6.16e+13      0.000    1.99e+08    1.99e+08
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                38.00
Prob(Q):                              0.91   Prob(JB):                         0.00
Heteroskedasticity (H):               6.99   Skew:                             0.20
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.49
===================================================================================
```

Port of Long Beach

SARIMAX Results

Dep. Variable:	TEU Vol	No. Observations:	144
Model:	SARIMAX(0, 1, 1)x(2, 0, [1, 2], 12)	Log Likelihood	-1685.285
Date:	Wed, 03 May 2023	AIC	3388.571
Time:	02:05:08	BIC	3415.236
Sample:	01-01-2010 - 12-01-2021	HQIC	3399.406
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
HOUST_Lag	23.0510	35.174	0.655	0.512	-45.890	91.991
CUSR0000SEHE_Lag	9.4782	217.132	0.044	0.965	-416.093	435.049
TOTALSA_Lag	-2427.3566	4417.432	-0.549	0.583	-1.11e+04	6230.652
ma.L1	-0.3155	0.095	-3.332	0.001	-0.501	-0.130
ar.S.L12	-0.0739	1.221	-0.061	0.952	-2.466	2.319
ar.S.L24	0.9250	1.068	0.866	0.386	-1.167	3.018
ma.S.L12	0.1677	1.374	0.122	0.903	-2.525	2.861
ma.S.L24	-0.8307	1.051	-0.790	0.429	-2.891	1.229
sigma2	1.084e+09	0.001	1.46e+12	0.000	1.08e+09	1.08e+09

Ljung-Box (L1) (Q):	0.50	Jarque-Bera (JB):	2.72
Prob(Q):	0.48	Prob(JB):	0.26
Heteroskedasticity (H):	1.51	Skew:	0.08
Prob(H) (two-sided):	0.16	Kurtosis:	3.65