Predicting and Planning for the Future: North American Truckload Transportation

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ABSTRACT

The trucking industry is crucial to the United States economy. An overwhelming majority of goods transported across the US are moved in trucks. For most companies, truck transportation is a prominent component that impacts their production, warehousing, customer service, and overall business performance. In fact, trucking constitutes one of the largest operational costs for a company. Trucking costs are highly volatile due to their association with the capricious freight industry and the US economy. Unexpected market fluctuations inevitably disturb companies' budget planning and operations, as well as impact their profits. This paper formulates a machine learning model to predict the US truckload dry van spot rate and a playbook of contingent actions. The model variables target and recognize the key elements in the trucking industry and the economy. Tested across 6 years of data, the model achieved an average MAPE below 7% and mean error below 0.05 for predicting 12 months in the future. The strong forecast accuracy allows companies to employ our playbook's strategic and tactical measures to mitigate risk and unplanned costs stemming from the volatility in the US trucking market.

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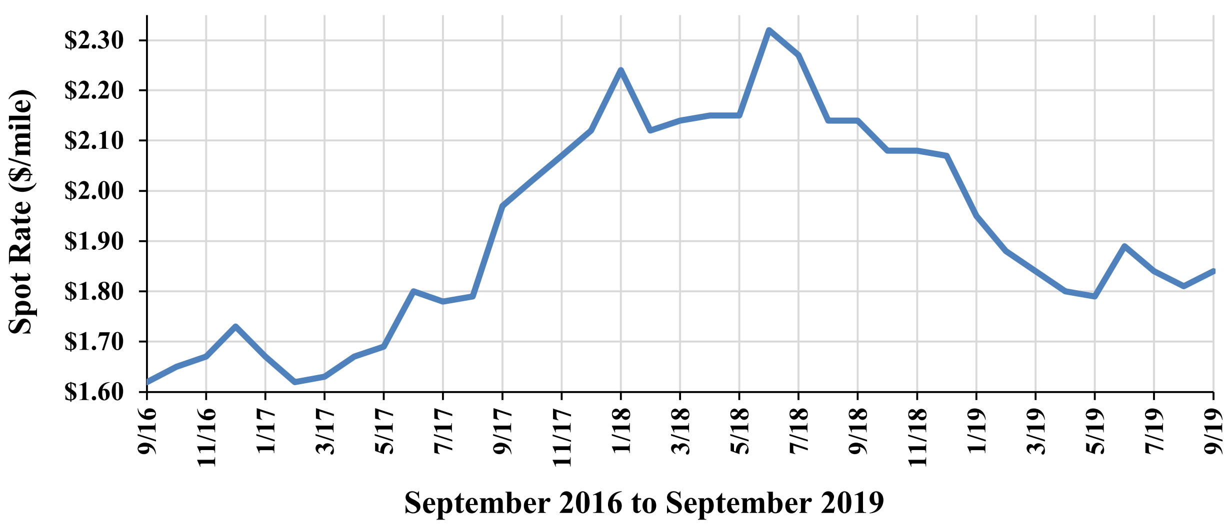
1 Introduction

The trucking industry is essential to companies and trade in the United States. Trucks are responsible for transporting nearly 70% of all goods moving throughout the country (McNally, 2019). Trucking transportation is inherently dynamic and flexible; enabling items to get to manufacturers and consumers rapidly while permitting shippers to constantly adjust to changing market conditions. An $800 billion industry (McNally, 2019), trucking has tentacles connecting stakeholders throughout the supply chain and is closely monitored by those involved. The economics of the industry are impacted by many internal and external factors resulting in constantly fluctuating market rates.

Shippers regularly establish contracts with carriers to reduce their exposure to the volatility of the trucking market. However, the trucking industry is unique in the sense that contracts are often non-binding in terms of volume and capacity commitments. Hence, carriers may reject a tendered load if they deem it advantageous to sell their capacity to the open market or they do not have their assets well positioned. There is no predetermined financial penalty to the carrier for failing to honor the contract, while it does damage the relationship with the shipper and may impact future business. Shippers track the carriers' service and they usually honor their contracts with shippers; however, carriers may jump to the open market when preferable rates are too good to ignore. At this point carriers will sell part of their capacity on the open market to obtain higher rates than those defined in their contracts leaving the shipper to look elsewhere for their needs.

Shippers regularly review their portfolio of carriers and closely monitor their performance. Carriers are typically graded by shippers across several areas, including cost, reliability, on-time delivery, customer service, and tender acceptance rate (TAR). The TAR measures the percentage of contracted truckloads (TL) that are accepted by carriers at the pre-set cost per mile (CPM). When tenders are rejected by carriers, companies are forced to explore alternative transportation options which typically incur higher costs. Rejections are more likely to occur during a tight market when the spot rate (market rate) is relatively high. Significant spot rate fluctuations can occur without warning and severely shock business operations (Bignell, 2013). A recent example depicting spot rate volatility was seen in 2017 and 2018. During this period, the average truckload CPM experienced a dramatic and unpredictable spike due to a rise in demand coupled with severe supply shortages devastating budgetary plans and profit margins (Murray & Glidewell, 2019). DAT Solutions, LLC (DAT) is an industry leader in monitoring trucking market activity and Figure 1 depicts this event through DAT's national dry van spot rates from September 2016 to September 2019.

Figure 1: DAT National Dry Van Spot Rate by Month



In Figure 1 the spot rate rises dramatically from early 2017 to mid-2018. An increased demand in trucking, led by the strong economy, caused the truckload transportation surge. Over this period the supply and overall truckload capacity was also significantly depressed due to the new Electronic Logging Device (ELD) mandate in 2017, fuel surcharges, insufficient equipment, and a national driver shortage (Johnson, 2018). This perfect storm of light supply and heavy demand resulted in record high spot rates as carriers sought to offset elevated operational costs as well as profit from the beneficial market conditions. Though the magnitude and factors may change, the inherent volatility of the trucking industry invariably leads to imbalances in the market.

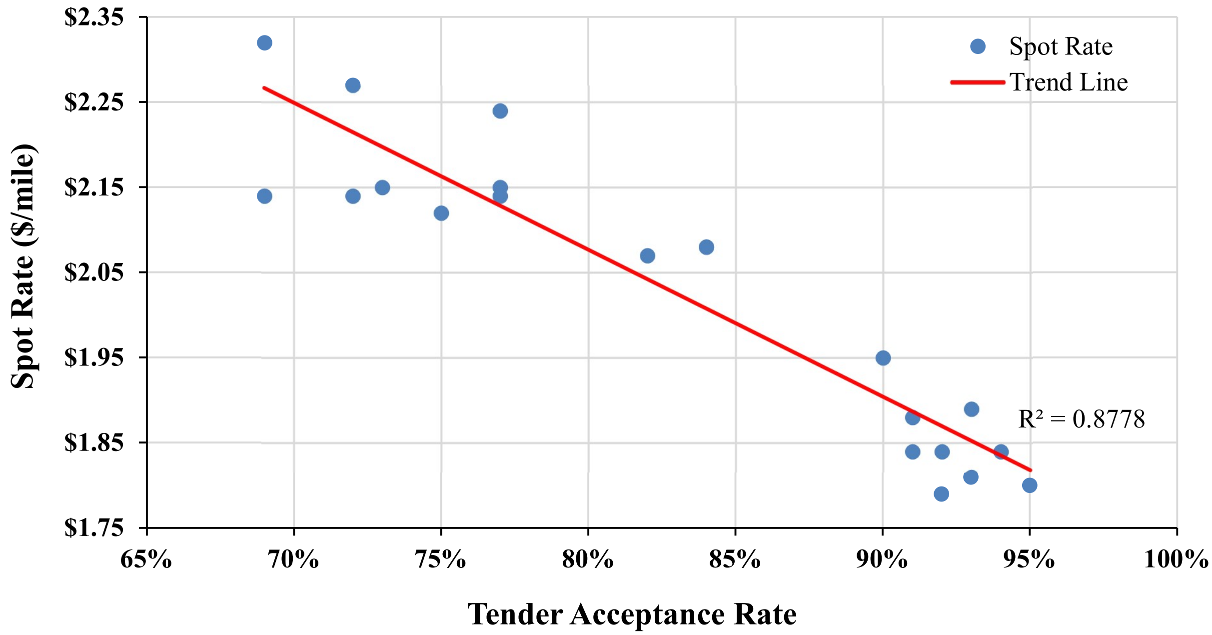
Our project focuses on improving companies' ability to navigate through trucking market imbalances. We developed a process to proactively plan and adjust transportation contracts to minimize costs and disruptions. Using a vector autoregression and ARIMA forecasting model, we are able to provide accurate insights into the trucking market over the coming 12 months. Our forecast links to a playbook of recommended actions for companies related to their trucking contracts and expected market conditions. Used together, these tools can reduce trucking costs as well as improve budget planning and business operations. The sections below provide more context on the trucking problems companies face as well as go in depth into the solutions we developed.

1.1 Problem Statement

For many companies, most of their operational costs are related to the transportation of cargo to distributors, warehouses, and customers. In 2017 and 2018, the companies throughout the US were caught off guard by the spike in transportation rates due to the conditions noted above. The tight market severely impacted their cash flow, operations, and profits. This project addresses companies' need to minimize future budget disruptions associated with significant and unexpected changes in the truckload transportation market.

As shown in Figure 2, the dry van truckload class 8 spot rate is inversely correlated to the freight tender acceptance rate of a large domestic shipper. When the spot rate increases, the company's freight tender acceptance rate decreases. Figure 2 depicts the relationships between the national spot rate (DAT) and the shipper's nationally averaged tender acceptance rate from January 2018 to September 2019.

Figure 2: Correlation between the DAT Monthly Nat. Spot Rate and TAR



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The downward line in Figure 2 is associated with a correlation of -0.94, indicating a strong negative correlation between the spot rate and TAR. As noted earlier, this inverse relationship is at least partially due to carriers seeking to maximize their profit margin and causes the freight cost of shippers to increase as they source alternative transportation (Bignell, 2013). The companies seek to improve their ability to anticipate these fluctuations in the spot rate and have an associated guide to inform tactical business decisions. Greater insight and preparedness will permit them to make adjustments prior to anticipated market shocks and lessen any negative impact on profits. Similarly, this capability allows companies to potentially increase margins when they know ahead of time that the market rate is expected to fall.

Short-term univariate and long-term multivariate forecasting models were developed in order to provide a 12-month outlook while also accounting for immediate disruptions to the domestic over-the-road trucking market. The two models complement each other in forecasting the spot rate over the coming year - in line with most shipper's planning cycle. This time horizon allows companies to execute short- and medium-term contingency plans associated with unexpected volatility in transportation costs.

This transportation problem is common among many companies in the US and has garnered great attention from the transportation industry and academia. Considerable research has been dedicated to this topic and to forecasting market rates. To this end, a variety of indexes, associated variables, and methods have attempted to achieve an accurate prediction of future spot rates. In an effort to improve on the current published predictions in the field, both univariate (ARIMA) and multivariate autoregressive (vector autoregression or VAR) machine learning techniques were used for the models developed. Further, the model has a unique composition of variables and 10 years of data capturing many historical market cycles. The variables and data selected target three critical areas: carrier operating costs, trucking market factors, and US economic forces.

The machine learning forecasts are accompanied by a tactical planning guide. The guide, or Tactical Playbook, provides options to shelter companies from forecasted cost increases and a decline in customer service due to increased tender rejection rates. The list of possible actions constitutes a playbook for general contracting strategy and mid-contract adjustments related to market conditions. Both the forecasting model and playbook will continue to evolve with new market data, changes in market players, as well as feedback from the results of actions implemented.

1.2 Relevance

The components of this project are expected to prove beneficial to a wide audience. The current model and recommended interventions will be valuable to companies moving truckloads of cargo within the US market. Specific regions or lanes can also be targeted through disaggregating the national level data set in order to apply localized interventions. In addition, the forecasting model can be expanded to other over-the-road transportation options such as tankers, flatbeds, or reefers. Further, the project methodology can be applied to other modalities such as rail, maritime, and air transport. The forecast model and playbook were designed for the transportation industry, but the approach developed to improve budget planning and future business operations is applicable across all sectors.

The remainder of this paper is structured as follows: in Section 2 we discuss the literature related to spot rate volatility and predictions in the trucking industry. Section 3 covers our methodology for developing our forecasting models. Section 4 focuses on the tactical playbook for guiding transportation contract decisions. Section 5 provides the results of our analysis and, finally, in Section 6 is our conclusion.

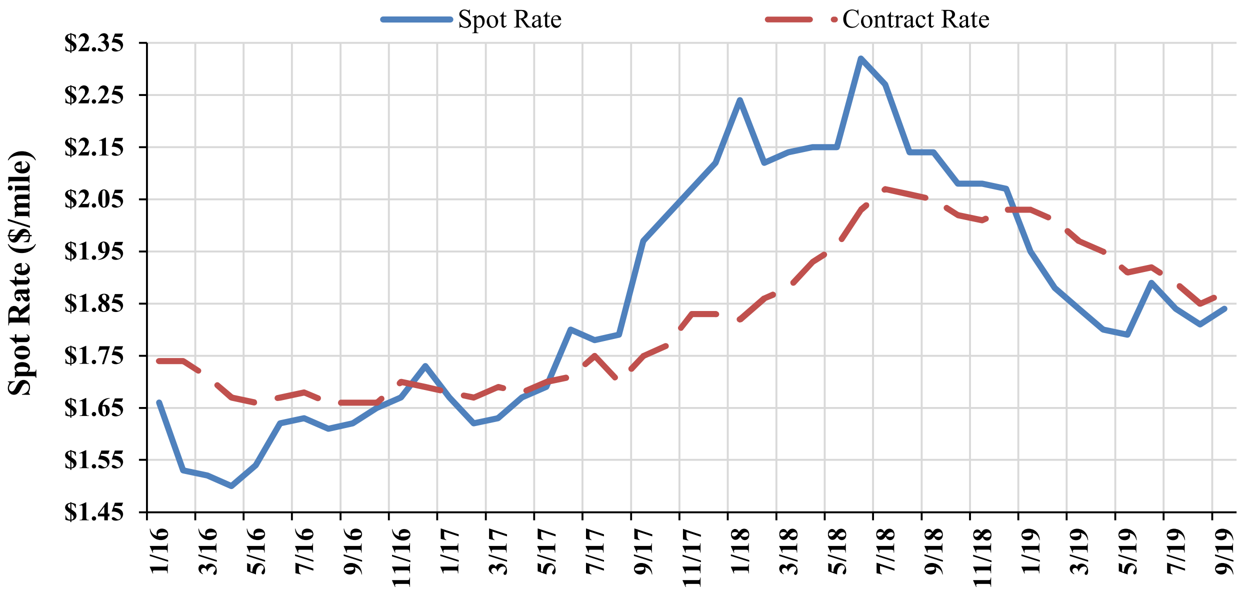
2 Literature Review

The transportation industry has garnered great attention across all sectors due to its important and widespread role in the US economy. Moreover, the cost per mile rate, its forecast, and its connection to the tender acceptance rate have been the subject of many industry and academic research projects.

The cost per mile (CPM) rate is the prominent indicator of US long-haul full truckload market conditions. The CPM varies across shipments based on several factors including the type of truck carrying the cargo, region, and contractual terms. The most widely used transportation equipment is the class 8 (CL8) dry vans (Bates, 2018). This research concentrates on analyzing the full truck load CL8 dry van market across the US. The CPM for this market is referenced in two forms: spot rate and contract rate. The former represents an average of the continuously fluctuating rates offered by carriers to shippers for transport at a specific point (spot) in time. The contract rate is a negotiated rate between carriers and shippers for specific lanes, typically 1 year in duration. For full truck loads from January 2016 to September 2019, Figure 3 charts the nationally averaged monthly spot and contract rates published by DAT.

Companies regularly solicit or tender for contracted rates to a large network of truckload carriers. The tender acceptance rate is the percent of loads that are accepted by the contracted carriers at the agreed upon CPM rates. When the spot rate increases, carriers are more likely to reject tenders at their contracted rates in order to earn more from the rates available on the spot market. Thus, shippers are forced to explore alternative truckload carrier options when market rates increase and subsequently, their transportation costs go up. As illustrated in Figure 3, this is precisely what happened in the US truckload market during 2017 into 2018. During that time, companies across the US were severely impacted by the sudden rise in transportation costs which disrupted their business operations, budget planning, and profit margins.

Figure 3: DAT Monthly National Spot and Contract Rate



January 2016 to September 2019

Accurate predictions of changes to the spot rate will provide companies with valuable time to adjust their operations and planning to mitigate any unexpected disturbances and associated losses. This research project focuses on developing a spot rate forecasting model and applying scenario planning tools specific to a domestic shipper's operational needs in order to reduce their exposure to shifts in the US trucking industry.

2.1 Spot Rate Forecast

Throughout the domestic trucking industry, there are many entities that gather key data points and apply their own analysis. This analysis provides insight for stakeholders throughout the supply chain to enhance planning and investment decisions. The spot rate is captured by several of these entities and due to varied sources and methodologies, these spot rates are not consistent. The diversity in data collection and data application, along with the numerous factors influencing the spot rate, contribute to the complexity of its prediction. Many researchers have explored this topic; however, the forecast modelling in this area is not exhaustive and there is room to explore alternative approaches to contribute to the existing body of work.

Bai (2018) used autoregressive integrated moving average (ARIMA) and nonlinear autoregressive with exogenous input (NARX) models to forecast short-term spot and contract rates on individual lanes. The input variables used included lagged values of spot and contract rates, and rates on adjacent routes and volumes. The results of the models were then compared based on the root mean squared error (RMSE) for both spot and contract rates using a 7-day ARIMA and a 53-day NARX rolling forecast. While the NARX model outperformed the ARIMA model for predicting the spot rates, both the ARIMA and NARX models performed similarly when predicting contract rates.

Miller (2018) also used the ARIMA method to forecast spot rates, but for a longer time horizon of 4 months. Miller used aggregated spot rate data from TruckStop.com for the period of January 2015 through August 2018. His forecast accuracy, measured by the coefficient of variation of the root mean squared deviations, was relatively high due to the aggregate nature of the data used in contrast to data dealing with individual lanes.

Bai (2018) and Miller (2018) inspired us to incorporate the ARIMA method into our forecasting model. As demonstrated in their papers, ARIMA models perform better in the short-term as opposed to a longer-term horizon. Based on this dynamic, our approach uses the ARIMA method to model short-term predictions and the vector autoregression (VAR) method for long-term forecasts. Together, both methods provide an accurate picture of expected changes to the spot rate over the coming year.

Rana (2019) analyzed several different forecasting methods and compared their ability to predict the short-term national and regional spot rates. The models examined include the Naïve model, Moving Average, Auto Regressive Integrated Moving Average, and Feed-Forward Neural Networks (FFNN). The forecasting accuracy of the national rates ranged from 6.7% to 7.5% MAPE over 1 to 8 week time horizons, while the regional accuracy ranged from 9.3% to 23.6%. The study found that the FFNN model outperformed the other models and that the national rate forecast was more accurate than the regional forecast.

A confidential research group, supporting a large multinational company, developed a forecasting model that uses a similar approach to our model. The group analyzed 14 aggregated transportation market and economic indicators through vector autoregression (VAR) to forecast the DAT national spot rate for 6 months in the future. The key variables incorporated include the Purchasing Managers' Index, Consumer Confidence Index, Class 8 Trucks Ordered, and trucking employment data from the Bureau of Labor Statistics. This approach was the launching point for our model development. We also incorporated the VAR method, although we were able to achieve greater forecasting accuracy with a smaller composition of endogenous variables.

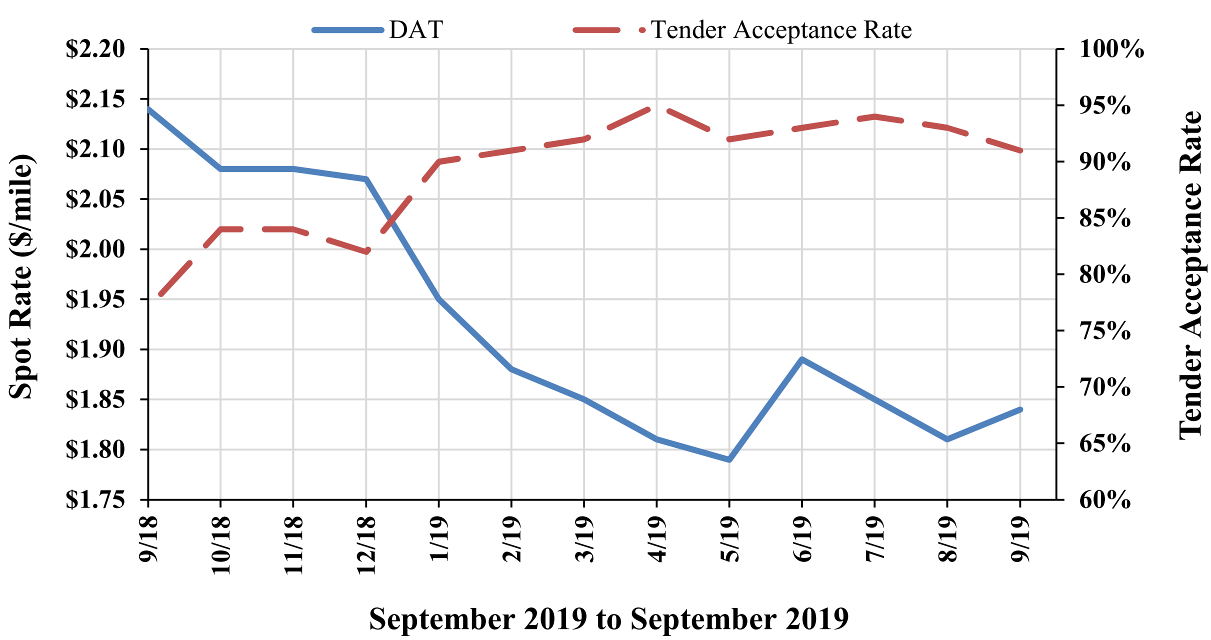
Mei, Liu, and Jing (2011) showed that VAR models are well suited for multivariate time series datasets and are able to yield accurate forecasts. Their work used 6 variables to forecast gross domestic product of the Shanghai region in China, namely fiscal revenue, social retail goods, secondary industry output, investment in fixed assets, employment rate, and tertiary industry output. The model proved significant with a small forecast error relative to other time series models.

Our research on spot rate forecasting led us to develop a short- and long-term machine learning approach to capturing future predictions of the trucking market. The VAR method was used due to its effectiveness with multivariate time series forecasting. Further, the ARIMA method was incorporated due to its accuracy on short-term predictions. Together, they provide a balanced picture of future market conditions and enhance the value of our Tactical Playbook. Our Tactical Playbook, covered in depth in Section 4, provides recommendations tailored to spot rate forecasts.

2.2 Tender Acceptance Rate

The tender acceptance rate (TAR) is a key metric for companies measuring how much of their truck transportation is executed at predetermined contract rates. Tenders for transport are provided to contracted carriers who can either accept the tender at the contracted rate or refuse the tender. Refused tenders are then subject to alternative (non-contract) shipping options which typically bring poorer customer service and associated costs as well as potential increases to transportation rates. Figure 4 exhibits the negatively correlated relationship between a large domestic shipper's tender acceptance rate (TAR) and the monthly national spot rate from DAT. As noted earlier and illustrated in Figure 2, this inverse relationship has a correlation of -0.94.

Figure 4: DAT Monthly National Spot Rate and Tender Acceptance Rate



The TAR is closely monitored by companies to manage their carriers and reduce their exposure to spot market volatility. Kafarski and Caruso (2012) found that on average the shipper pays 13% more than primary carrier rates when shipments are rejected.

Similarly, Aemireddy and Yuan (2019) found that rates increase by 12% when rejected by primary carriers and by 35% when rejected by all routing guide options. They interviewed the shipper's carriers and brokers, and listed the main reasons for tender rejections as follows: 1) reduced lead time, 2) extended dwell times at both the place of origin and destination, 3) inconsistent freight lane activity, 4) surges in volumes on certain lanes, and 5) contracted rates below the market.

Caldwell and Fisher (2008) also found that long lead time was correlated with high transportation costs. They worked with C. H. Robinson's Transportation Management Center and analyzed more than 1 million truckload transactions from 2007 to 2008 in order to identify correlations between factors impacting transportation costs. Their work noted several underlying factors that could be leveraged, to include tender lead times, corridor volume, and carrier size preference. They categorized lead time buckets from 1 day to 5 days and found that the customers with transactions of 5-day lead times paid $42 less on average (4.2% of annual transportation costs) than the customers with only 1 day of lead time.

The results from the papers cited above reinforce the connection between tender lead times and tender acceptance rates. Hence, initiatives focusing on increasing tender lead times should reduce tender rejection rates and trucking transportation costs.

Kim (2013) also identified a strong correlation between truckload costs and rejection rates. The study used linear regression to identify significance of factors impacting tender rejections, variables including average of length of haul (ALOH), price differential of shipper/market price, geography, and variability of volume. Kim found that on average the truckload costs increased by 14.8% when a load was rejected and also that volume variability has a positive correlation with tender rejections for lanes with ALOH under 100 miles.

Ostensibly, Kim's finding challenges our analysis in Figure 2 that showed a negative correlation between TAR and the spot rate. However, Kim's study points to the complexity of the trucking industry and the diverse dynamics that are found across varied market segments and geographies.

Mentioned above, Aemireddy and Yuan (2019) used OLS multiple linear regression to identify a relationship between cost per load and key trucking metrics. Variables studied include distance, lead time, corridor volume, lane consistency, lane volatility, weekend shipment, quarter end shipment, and key regions. Their work targeted predicting the probability of tender acceptance and the probability of routing guide failure based on varied shipments attributes. Analysis from their data set discovered that 1) longer lead times (> 5 days) saved $13.66 per load, 2) high corridor volumes saved $25.24 per load, 3) high lane consistency saved $5.72 per load, and 4) high lane volatility cost $22.08 per load. These numbers were from one firm and results will vary from company to company. The authors highlight the importance of shippers working closely with carriers and the 4 key metrics listed above being used to optimize cost savings.

Similar to our project, Sinha and Thykandi (2019) focused on improving the tender acceptance ratio for shippers through reducing the gap between spot and contract rates. Their work involved a non-linear model to create dynamic contract rates based on the DAT national spot index and optimize the number of shipments that switch from the spot market to contracted carriers. Data for the tail lanes (lanes with weak or intermittent demand) of 12 origin warehouses was analyzed and cost savings were identified for 2 of the 12 locations for the client company. Sinha and

Thykandi showed that an index-based model can be used to improve TAR even in tight market conditions. Albeit through a different approach that will be described below, our project also provides recommendations for reducing the freight auction percentage of truckloads in order to control costs.

Our research reviewed and analyzed many key trucking factors outlined above. Specifically, spot and contract rate dynamics, tender lead times, lane demand, and lane consistency. We examined the characteristics of our client's transportation network and studied business practices and challenges. These insights, coupled with our industry research, informed our guide of recommended contractual actions tailored to current and expected market conditions. The Tactical Playbook, combined with our forecasting models, will better enable companies to weather shocks to the trucking market through strategically reducing risk and realizing cost savings.

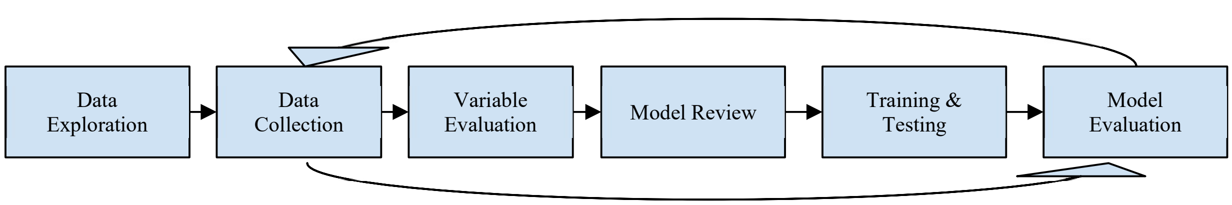
3 Forecasting Methodology

This section describes long-term and short-term machine learning forecasting models developed to predict the national trucking spot rate over 12 future monthly periods. The long-term forecast and associated vector autoregression (VAR) method is described initially, followed by the short-term forecast employing the autoregressive integrated moving average (ARIMA) method.

3.1 Forecast Model

The forecast model was developed through a series of stages. First, driven by industry research, we explored various metrics and data points that may provide insight into predicting national spot rates. Second, all the data variables of interest were collected over the longest historical ranges available and processed for analysis. Third, the data underwent econometric testing to narrow the field of variables and reduce dimensionality. Next, several forecasting methods and varied compositions of variables were reviewed. Then once the most promising forecasting method was selected, the data set was split into a number of training and testing sets for model validation. Finally, the method was evaluated based on how it performed on the different testing sets. The process involved many iterations before the final forecasting method and final list of variables were selected for the model. Figure 5 outlines the steps taken to develop the model which are described in more detail in the succeeding sections.

Figure 5: Model Flow Chart

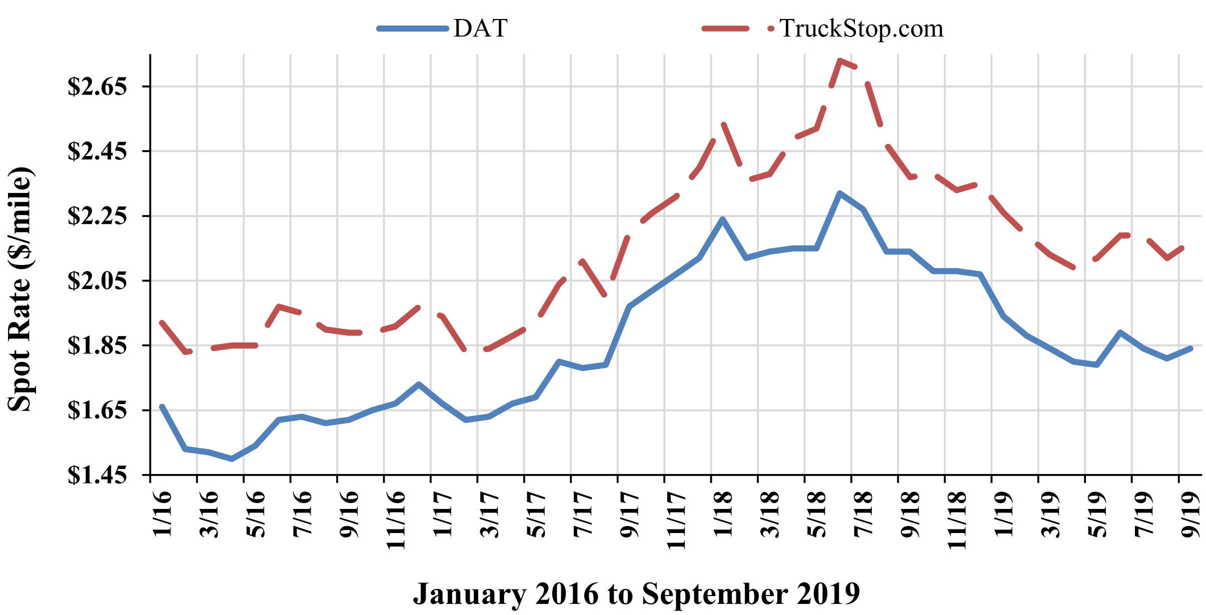


3.2 Data Exploration and Collection

The trucking industry is often viewed as a leading indicator of the US economy (Premack, 2019). The development of the forecast exploited that connection through concentrating on variables that measure change in the state of the economy and the trucking market. The trucking variables that were considered focused on class 8 dry van data as dry vans – compared to tankers, flatbeds, or reefers – represent the most common type of truckload freight transportation (Stinson, 2019). Further, data was gathered capturing market activity across the country in order to best forecast for the spot rate on a national level.

Several organizations report the national spot rate, and each has different sources and methods of measurement. This lack of consensus results in significant differences in published spot rates depending on the publisher. Figure 6 depicts two monthly national spot rates over the past three years. The spot rates are from two different industry load boards - DAT and TruckStop.com.

Figure 6: Comparison of Monthly National Spot Rates



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The two rates exhibited above follow market fluctuations almost identically and have a strong positive correlation of 0.98. Nevertheless, over the same time period a clear distinction is seen between the two monthly national spot rates. Considering the significant differences with spot rate data among varied sources, one source needed to be selected as a benchmark for the project. At the request of the client, the nationally average spot rate from DAT was chosen for the forecasting model.

Data sets were considered from a wide variety of resources to find variables with the ability to explain changes in the national spot rate. The initial set of variables were gathered from three key areas: 1) US trucking industry operational costs, 2) US trucking market indicators, and 3) US economic indicators. Sources of the data include the Bureau of Labor Statistics, Bureau of Economic Analysis, US Department of Agriculture (USDA), Federal Reserve Economic Data (FRED), DAT, TruckStop.com, FTR Transportation Intelligence, Cass Information Systems, and ACT Research, Co.

In order to strengthen the training component of the machine learning model, relatively long historical ranges of data were pursued during the exploration phase. The final model is based on over 10 years of data for all variables from January 2009 to present. Further, to reduce noise for the long-term forecast, all the data variables have a monthly frequency as opposed to daily or weekly.

Once the preliminary data set was determined, adaptations of the variables were also considered. Time lags as well as quadratic versions of the variables were evaluated for inclusion in the forecasting model.

3.3 Variable Evaluation

The variables considered for the model are listed in Table 1 with their associated domain and source.

Table 1: List of Potential Model Variables

Area	Variable	Source
Industry Operational Costs	Trucking Employees	Federal Reserve Economic Data
	Producer Price Index: Trucking Sector	Bureau of Labor Statistics
	Trucking Employees Hourly Earnings	ACT Research
	Average Weekly Hours, Diesel Price	ACT Research
Market Indicators	Intermodal Price	CASS
	Cass Truckload Linehaul Index	CASS
	Cass Shipments Index	CASS
	Cass Expenditure Index	CASS
	DAT Load-Truck Ratio	DAT
	Class 8 Net Orders	ACT Research
	Class 8 Retail Sales	ACT Research
US Economic Indicators	Commodity Total for Price Received	University of Michigan
	Food Commodities	USDA
	Consumer Price Index	USDA
	Export Price Index	USDA
	Import Price Index	Bureau of Economic Analysis
	Industrial Production	Federal Reserve Economic Data
	Composite Leading Indicator	Federal Reserve Economic Data
	Producer Price Index	Federal Reserve Economic Data
	Unemployment rate	Federal Reserve Economic Data
	Consumer Sentiment, University of MI	Federal Reserve Economic Data

The prospective variables in Table 1, as well as their lagged and quadratic versions, underwent an initial correlation screening to be considered for the model. The Pearson Correlation Coefficient (r), ranging from -1 to +1, measures the association between the continuous variables. An absolute r value of 0.2 is considered the minimum benchmark to suggest a medium to large correlation (Funder, 2019). R values between -0.2 and 0.2 for variables correlated to the spot rate were discarded. Further, an absolute value of 0.90 is considered the maximum correlation (r) benchmark for redundancy analyses and multicollinearity reduction (Hair, 2013). Hence, variables were evaluated in a cross-correlation matrix and when two variables had a r value greater than

0.90, the variable with the weaker correlation to the spot rate was discarded. Finally, the probability value (p-value) of the variables was evaluated in line with Fisher (1950) who argued that p-values should not exceed 0.10. Therefore, variables with a p-value greater than 0.10 were discarded due to not having a statistically significant association with the spot rate.

Variables that passed the initial screening were then evaluated based on their collective ability to explain variance in the spot rate. They were analyzed through stepwise regression analysis where data points were successively evaluated based on their contribution to the model. The adjusted R^2 was used in comparing the various data set groupings. A number of different combinations were iteratively tried in order to yield the highest adjusted R^2, or multivariate explanation for changes in the spot rate. The Variance Inflation Factor (VIF) was another parameter used in the process. VIF, defined as $1/(1-R^2)$, generally should not exceed 10 at which point regression results may become unreliable due to correlation with other predictors (Yoo, 2014). Therefore, to guard against multicollinearity, only models with a VIF below 10 were examined further.

The process outlined above reduced the prospective 56 variables – with lag and quadratic versions - to 4 variables. These 4 selected variables and the DAT spot rate constituted the five endogenous variables of the VAR forecasting model. To ensure the fitness of the model, it was subject to several diagnostic checks. These tests, described below, include autocorrelation, autoregressive conditional heteroscedasticity (ARCH), stationarity, and cointegration.

3.4 Model Variables

The endogenous variables selected for the VAR forecasting model are defined here.

1. DAT Spot Rate: The daily dry van CL8 spot rate published by DAT, excluding the fuel surcharge, aggregated by month.

2. DAT Load-to-Truck Ratio: The number of loads posted for every truck posted on DAT Load Boards.

3. Export Price Index: Crop Production[2]: Measures changes in the price of goods and services related to domestically grown crops sold outside the US.

4. Producer Price Index: Measures the change in prices received by US producers for their output.

5. Composite Leading Indicator[2]: A subset of the main economic indicators that are designed to provide early signs of changes in the US economy.

VAR was selected because of the superior accuracy and minimal bias achieved through this method. An Ordinary Least Square model (OLS) could also have been performed on the model. In the OLS model, the spot rate is designated as the dependent variable and the other variables listed above are designated as the independent variables. If performed on the entire data set, the OLS model achieves an adjusted R^2 of 0.7. Further, the probability values (p-value), measuring the statistical significance of the variables in the OLS model, are shown in Table 2.

Table 2: OLS Model P-Values

Variable	P-Value
DAT Load to Truck Ratio	< .01
Export Price Index: Crop Production	< .01
Producer Price Index	< .01
Composite Leading Indicator	< .01

In linear regression a relationship is estimated between the independent variables and the dependent variable by minimizing the sum of the squares of the differences between the observed and predicted values of the dependent variable. In our OLS model, with an adjusted R^2 of 0.7, the designated independent variables explain 70% of the variability in the dependent spot rate around the mean. While 70% represents a significant explanatory correlation, with identical data the VAR method achieved superior results, as displayed in Table 3.

Table 3: Adj. R^2 of VAR Equations

VAR Equation	Adj. R^2
DAT Spot Rate	0.97
DAT Load to Truck Ratio	0.77
Export Price Index: Crop Production	0.94
Producer Price Index	0.93
Composite Leading Indicator	0.99

The vector autoregression (VAR) method differs from OLS in the relationship between the model variables. In a VAR model, the variables of interest are all treated as dependent or endogenous variables (Abdulnasser, 2009). Table 3 shows the results of the 5 equations involved in our VAR model and their ability to explain the changes in each of the endogenous variables. The DAT Spot Rate equation has an adjusted R^2 of 0.97 indicating that the equation can explain 97% of the variability in the spot rate. VAR models perform well forecasting multivariate time series for stationary data sets and typically outperform univariate time series in this context (Mercy & Kihoro, 2015). The following section further explains the VAR method and model testing.

3.5 Vector Autoregression Model

Vector autoregression (VAR) uses linkages between multiple variables throughout a time series. VAR captures the predictions of endogenous variables by calculating their own lagged values, the lagged values of the other endogenous variables, as well as the value of the errors (Mohr, 2018). In our VAR model there are 5 endogenous variables and, therefore, 5 linked time series that influence each other. Hence, our model consists of a system of 5 equations, 1 equation per endogenous variable. Equation 1 illustrates the VAR system of equations.

Equation 1: VAR Model Equations

$$
\begin{aligned}
Y_{1,t} &= \alpha_1 + \beta_{11,1}Y_{1,t-1} + \beta_{12,1}Y_{2,t-1} + \beta_{13,1}Y_{3,t-1} + \beta_{14,1}Y_{4,t-1} + \beta_{15,1}Y_{5,t-1} + \varepsilon_{1,t} \\
Y_{2,t} &= \alpha_2 + \beta_{21,1}Y_{1,t-1} + \beta_{22,1}Y_{2,t-1} + \beta_{23,1}Y_{3,t-1} + \beta_{24,1}Y_{4,t-1} + \beta_{25,1}Y_{5,t-1} + \varepsilon_{2,t} \\
Y_{3,t} &= \alpha_3 + \beta_{31,1}Y_{1,t-1} + \beta_{32,1}Y_{2,t-1} + \beta_{33,1}Y_{3,t-1} + \beta_{34,1}Y_{4,t-1} + \beta_{35,1}Y_{5,t-1} + \varepsilon_{3,t} \\
Y_{4,t} &= \alpha_4 + \beta_{41,1}Y_{1,t-1} + \beta_{42,1}Y_{2,t-1} + \beta_{43,1}Y_{3,t-1} + \beta_{44,1}Y_{4,t-1} + \beta_{45,1}Y_{5,t-1} + \varepsilon_{4,t} \\
Y_{5,t} &= \alpha_5 + \beta_{51,1}Y_{1,t-1} + \beta_{52,1}Y_{2,t-1} + \beta_{53,1}Y_{3,t-1} + \beta_{54,1}Y_{4,t-1} + \beta_{55,1}Y_{5,t-1} + \varepsilon_{5,t}
\end{aligned}
$$

where each equation Y_i are endogenous variables at time t, α is the intercept, β are coefficients of the lags of Y until order p, and ε_t is the error term. Equation 1 shows the model system for a lag order of 1 where lag values are included from 1 previous time period ($_{t-1}$). Our VAR model uses a lag order of 5 and includes the lag values from 5 previous time periods. Further, our VAR model is Dynamic, meaning that it incorporates a forecasted period to inform the next forecasted period as opposed to being Static and using the same parameter for all forecasted periods. In Equation 2 we wrote the complete equation of 1 endogenous variable, Y_1, incorporating a lag order, p, of 5.

Equation 2: VAR Equation with 5 lag order

$$Y_1 = \alpha_1 + \beta_{11,1}Y_{1,t-1} + \beta_{12,1}Y_{2,t-1} + \beta_{13,1}Y_{3,t-1} + \beta_{14,1}Y_{4,t-1} + \beta_{15,1}Y_{5,t-1} + \beta_{11,2}Y_{1,t-2} + \beta_{12,2}Y_{2,t-2} + \beta_{13,2}Y_{3,t-2} + \beta_{14,2}Y_{4,t-2} + \beta_{15,2}Y_{5,t-2} + \beta_{11,3}Y_{1,t-3} + \beta_{12,3}Y_{2,t-3} + \beta_{13,3}Y_{3,t-3} + \beta_{14,3}Y_{4,t-3} + \beta_{15,3}Y_{5,t-3} + \beta_{11,4}Y_{1,t-4} + \beta_{12,4}Y_{2,t-4} + \beta_{13,4}Y_{3,t-4} + \beta_{14,4}Y_{4,t-4} + \beta_{15,4}Y_{5,t-4} + \beta_{11,5}Y_{1,t-5} + \beta_{12,5}Y_{2,t-5} + \beta_{13,5}Y_{3,t-5} + \beta_{14,5}Y_{4,t-5} + \beta_{15,5}Y_{5,t-5} + \varepsilon_{1,t}$$

Equation 2 represents only 1 variable. The complete VAR model consists of 5 interrelated equations similar to Equation 2 that are set to a lag order of 5.

3.5.1 VAR Model Validation

Diagnostic checks were performed on the VAR model to determine if the model was appropriately fit. First, the model was analyzed to determine the optimal lag order. Then econometric tests inspected the presence of white noise, the model consistency, and the model stability. The econometric tests and results are described in the following sections.

3.5.2 Variable Lag Determination

Econometric software (Gretl) analyzed the multivariate time series data to determine the optimal lag length to be used for the model. The information criteria (IC) methods used included the Akaike Criterion (AIC), Schwarz Bayesian Criterion (BIC), and Hanna-Quinn Criterion (HQC). The AIC, BIC, and HQC measure the goodness of fit of a statistical model and Table 4 displays their lag orders measurements.

Table 4: Lag Order Determination

Lag	AIC	BIC	HQC
1	27.61	29.67	28.45
2	26.98	**29.61***	28.05
3	26.98	30.18	28.28
4	26.521	30.29	28.05
5	26.02	30.367	**27.79***
6	26.01	30.92	28.00
7	26.08	31.57	28.31
8	26.15	32.21	28.62
9	26.16	32.79	28.85
10	26.15	33.35	29.08
11	**25.90***	33.68	29.06
12	26.07	34.41	29.46

Lags ranging from 1 to a maximum of 12 were examined under each criterion in accordance with our monthly times series data set. The optimal lag value for each criterion are bolded in Table 4. The AIC indicated an optimal lag of 11, the BIC indicated an optimal lag order of 2, and the HQC indicated an optimal lag order of 5 for the model. For our VAR model we used the median lag order recommended and, therefore, a lag order of 5. Our IC selection is supported by Shittu & Asemota (2009) who found that the HQC performs well in selecting the lag order of an autoregressive model for larger times series.

3.5.3 Autocorrelation: Durbin Watson and Portmanteau tests

The VAR model coefficients can be described as a filter that transforms white noise into structured data (SSCN, 2020). If a model fails to fully capture correlations in the data set, white noise or autocorrelation will be present. The presence of autocorrelation can bias the standard error and lead to inaccurate interpretations of the significance of predictors (Statistics, 2020).

The Durbin Watson test analyzes the residuals of regression analysis for autocorrelation found in each equation of the VAR model. Table 5 exhibits the test statistics for the equations.

Table 5: Durbin Watson Test

Equation	Result
DAT Spot Rate	2.06
DAT Load to Truck Ratio	2.00
Export Price Index: Crop Production	2.05
Producer Price Index	2.05
Composite Leading Indicator	1.52

Durbin Watson test results between 0 and 2 indicate a positive autocorrelation, results between 2 and 4 indicate a negative correlation, and results of 2 indicate that there is no autocorrelation. Four equations center closely around 2 with the Composite Leading Indicator equation at 1.52, indicating a modest positive autocorrelation. This is common with time series data and values between 1.5 and 2.5 are considered relatively normal (Statistics, 2020). Therefore, significant autocorrelation is not present in the VAR model equations and we fail to reject the null hypothesis.

The portmanteau-test of Box and Pierce (1970) evaluates equations in the VAR model for autocorrelation as a group. The test looks for the presence of white noise in the residuals of coefficient estimates. The portmanteau Box-Pierce test statistic for the VAR model is < .01, rejecting the null hypothesis at the 1% significance level, indicating that there is no white noise in the model.

3.5.4 Autoregressive Conditional Heteroscedasticity (ARCH)

The multivariate ARCH test examines the model for heteroscedasticity or uniformity in the variance of the error terms (Kenton, 2019). The presence of heteroscedasticity can be 'interpreted as evidence of misspecification' (Engel, 1982, p. 990). The ARCH test statistic is 0.08 for the VAR model with a lag order of 5. The test statistic is below the 10% significance level and the model fails to reject the null hypothesis indicating that there is no heteroscedasticity.

3.5.5 Stationarity

Stationarity is an important characteristic for vector autoregression modeling, where the times series mean and variance should not change over time. Initially, we reviewed the eigen functions which represent the stationary state of a system (SSCN, 2020). The eigenvalues corresponding to each VAR equation are displayed in Table 6.

Table 6: Eigenvalues

Equation	Result
DAT Spot Rate	0.16
DAT Load to Truck Ratio	0.73
Export Price Index: Crop Production	0.97
Producer Price Index	1.91
Composite Leading Indicator	1.23

The VAR model system is stable and stationary if all equations have an eigenvalue < 1 (SSCN, 2020). Table 6 illustrates that the Producer Price Index and Composite Leading Indicator are above the threshold. The Augmented Dickey-Fuller (ADF) test was used to further explore stationarity in the model.

The ADF test examines model stationarity by testing the unit root of each endogenous variable. Table 7 displays the ADF test results.

Table 7: ADF Test

Variable	P-Value	Result
DAT Spot Rate	0.25	Fail to reject the null
DAT Load to Truck Ratio	0.06	Reject the null at 0.10
Export Price Index: Crop Production	0.46	Reject the null at 0.10
Producer Price Index	0.04	Reject the null at 0.10
Composite Leading Indicator	0.37	Fail to reject the null

The null hypothesis in the ADF test states that a variable is not stationary. The DAT Spot Rate, Export Price Index, and the Composite Leading Indicator failed to reject the null hypothesis indicating the presence of non-stationarity and instability. To control for stationarity, an exogenous Time Trend was incorporated into the VAR model.

3.5.6 Engle-Granger Cointegration Test

The cointegration test looks for a statistically significant connection between two or more variables. Problems related to unit root and statistical inference are associated with cointegration (Watson, 1994). The Engle-Granger Cointegration test has two components. The first corresponds to the ADF test displayed in Table 7 and the p-values of the unit roots for each endogenous variable. The second component relates to the stationarity of the residuals from the cointegration regression. The Gretl software yields a p-value of 0.72 for the stationarity of these residuals which is greater than a 10% significance level and fails to reject the null hypothesis.

There is cointegration in a model if the ADF test is not rejected for the endogenous variables and the ADF test is rejected for the regression residuals. Both of these conditions are not met for our VAR model and, therefore, there is no evidence of cointegration.

3.5.7 VAR Training and Testing

The time series data and relationships between the endogenous variables meet the criteria for forecast modeling. The VAR model diagnostics verified consistency, stability, and an absence of white noise. The model passed autocorrelation and cointegration tests and includes a Time Trend exogenous variable to reinforce stationarity. Monthly exogenous dummy variables were also added to the model to control for seasonality.

The complete VAR model, consisting of 5 endogenous variables and 12 exogenous variables, was systematically trained, and tested to evaluate model accuracy and bias. The model evaluation concentrated on the endogenous DAT spot rate variable. Our VAR system developed equations for all 5 endogenous variables; however, the predictability of spot rate is the target of this project and the predictability of the other equations is not directly reviewed.

The 10-year data set was separated into 11 different training and testing set combinations over a 6-year period. The testing sets were equivalent in length and consisted of 12 monthly observations or 1 year of predictions. Further, the testing sets were defined every 6-months from April 2014 to March 2020. The training sets accompanying the testing sets consisted of observations from the beginning of the data set, January 2009, to 1 month prior to the start of each testing set. The number of observations being evaluated ranged from 63 to 123 observations.

The testing sets of the model were measured by mean absolute percent error (MAPE) for accuracy. Further, forecasting bias in the model was measured by mean error. Section 5 displays the VAR model tests and the accompanying results.

3.6 ARIMA Model

The VAR model explained above provides a long-term spot rate forecast. The monthly frequency of the VAR data set reduces white noise, but also reduces short-term predictive abilities. The unsuitability of our VAR model for short-term forecasts is furthered by the delayed availability of the most recent data points. Of the 5 endogenous variables, only one is available in real-time (spot rate), the other variables can have a delayed release of several weeks. Therefore, if a significant event occurs impacting the trucking market (e.g. hurricane, labor strike, CoVID-19), the effect may not be realized in the VAR model forecast for up to two months.

The autoregressive integrated moving average (ARIMA) method addresses the short-term forecasting need. Similar to the VAR model, the ARIMA method uses time series data and lagged observations for informing future predictions. While the VAR method is meant for stationary data, the ARIMA method is suited for non-stationary series. In fact, the 'integrated' part of ARIMA refers to how the method subtracts an observation from a previous observation (differencing) to institute stationarity into a data set (Hyndman & Athanascopoulos, 2018).

Our ARIMA method employs univariate analysis time series data to predict the dependent variable – the monthly national DAT spot rate. Table 8 exhibits the summary statistics of the spot rate time series.

Table 8: DAT's Monthly National Spot Rate ($/mile)

Mean	1.44
Median	1.42
Minimum	1.09
Maximum	1.99
Standard Deviation	0.202
Covariance	0.14
Skewness	0.39
Valid Observations	135

Due to the immediate availability of the spot rate, the ARIMA data range is larger than the VAR time series and goes from January 2009 to March 2020. The data set consists of 135 observations, above the 100 minimum recommended number of observations for ARIMA modeling (Box & Tiao, 1975). Equation 3 depicts the ARIMA model.

Equation 3: ARIMA Equation

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \phi_2 \varepsilon_{t-2} + \ldots + \phi_q \varepsilon_{t-q}$$

where t represents the time period, α is the intercept, β is the coefficient of the lag(s), ϕ is the coefficient of the error term, and ε represents the error term.

3.6.1 ARIMA(p, d, q)

An ARIMA model has three key parameters: the lag order (p), the degree of differencing (d), and the order of moving average (q) (Brownlee, 2019). A p of 4 was selected to align with the 3-month (quarter) forecast. Further, the Augmented Dickey-Fuller (ADF) Test resulted in a p-value of < .01 for the 1st difference of the spot rate, allowing for d to be set at 1. In addition, with our ARIMA model targeting the 2-month lag in our VAR model, a q value is set to 2. Therefore, the ARIMA(p,d,q) method for this forecast is defined as ARIMA(4,1,2).

3.6.2 Diagnostic Check

The fitness of the ARIMA model was validated through a series of diagnostic checks. These checks closely relate to the VAR method tests. Below, the ARIMA method is checked for autocorrelation, stationarity, and heteroscedasticity.

3.6.3 Autocorrelation

Akin to the portmanteau-test performed on the VAR model (Section 3.5.3), the Ljung-Box test looks for white noise or randomness in a model (Box & Pierce, 1970). The Ljung-Box test is often used in ARIMA methods and tests the residuals from the ARIMA model for autocorrelation. The p-value of the Ljung-Box test on the model is 0.02 and below the significance level of 5% indicating that the null hypothesis is rejected and there is no autocorrelation.

3.6.4 Stationarity

The Augmented Dick-Fuller test for stationarity used earlier on the VAR method is repeated for the ARIMA model. For the ARIMA model, since it is univariate, the ADF test is only performed on the unit root of the spot rate. Table 9 shows the ADF test statistic for the spot rate and 1st difference of the spot rate.

Table 9: Augmented Dickey-Fuller Test

Variable	P-Value	Result
Spot Rate	0.29	Fail to reject the null
1st Difference of Spot Rate	0.001	Reject the null at 0.05

The p-value of the spot rate is above a 10% significance level and fails to reject the null hypothesis and is not stationary. The first difference of the spot rate is stationary as it is below the significance level and rejects the null hypothesis. The ADF test supports the designation of d to 1 in the ARIMA(4,1,2) model parameters.

3.6.5 Autoregressive Conditional Heteroscedasticity (ARCH)

The ARCH test was applied to identify the presence of heteroscedasticity in the model. The p-value is 0.003 and below the 5% significance level. The ARIMA model fails to reject the null hypothesis indicating that there is no ARCH effect or heteroscedasticity.

3.6.6 ARIMA Training and Testing

The diagnostic testing demonstrated that the ARIMA method is fit for forecasting the spot rate. Further, the testing supports the selected p, d, q parameters for the ARIMA(4,2,1) model.

The ARIMA model was developed for short-term monthly level forecasts. It predicts 3 monthly observations into the future to account for the lag of the VAR model. The ARIMA model was evaluated similarly to the VAR model apart from the length of the testing sets which are 3-month ranges. In addition to evaluating the ARIMA testing forecasts, the differences between the ARIMA and the VAR model over the 3 forecasted months were recorded and evaluated. The testing results of the ARIMA model are found in Section 5.

4 Tactical Playbook

This chapter explains the second portion of the methodology involving the Tactical Playbook. Prior to delving into the details of the playbook, we will provide an overview of a typical shipper's two-step contracting process.

The initial step is carrier screening. This involves identifying qualified carriers based on their geographic scope, shipping capacity, financial stability, and historical performance. The second step is a procurement event where specific lanes, or a group of lanes, are assigned to carriers through a competitive process. Each lane can be assigned to one carrier (primary carrier) or several carriers (e.g. secondary, tertiary carriers). The list of all carriers assigned to particular lanes and their relative ranking is referred to as the *routing guide*. The routing guide is fed into the shipper's transportation management system and is used during the tendering process.

Contracts with carriers typically involve projected volumes and rates in cost per mile as well as predetermined accessorial unit costs. When the shipper needs to transport cargo, the shipper tenders the associated volume to the contracted carriers. During the tendering process, the carriers have the option to accept the tender or reject the tender, which is more common during tight markets. In some cases, tender rejections could be due to the demand exceeding the available supply or could be from carriers seeking to sell their capacity for higher rates on the open market. When tenders are rejected by contracted carriers, shippers will tender loads to the next carrier in the routing guide. If all the carriers in the routing guide reject the tender, then the loads are auctioned on the spot market where rates are more volatile and service levels are often less reliable.

To guard against higher costs and lower service levels, we developed a playbook for shippers applicable to varied market conditions. The playbook works tangentially with our forecasting model and can inform shippers on tactical actions to consider based on predicted spot rates. The remainder of Section 4 will outline the elements of the playbook, and in Section 5 we will define when and how they are implemented.

4.1 Overview of Strategies

Our playbook covers strategies that companies can use for contracting trucking transportation as well as tactical actions companies can take during contract cycles. The decisions and their respective timing are based on current and expected market conditions. This section defines considerations and options for the shipper in three phases: planning, contracting, and tactical.

4.2 Planning Phase

Preplanning and management of procurement events are critical components of effective transportation sourcing. Below is a list of measures shippers can take to enhance the performance of their carriers.

1. Carrier Targeting: Transportation needs vary across a network. Continuous research on carriers and their capacity throughout a shipper's network is recommended. Shippers should define and rank their metrics for evaluating a carrier and create preferred carrier profiles. Bid processes are typically more effective with targeted carriers as opposed to involving a larger field with unvetted candidates (Strickland, 2020).
2. Dwell Time Reduction: Shippers should put in place metrics to capture dwell time at shipping and receiving locations and continuously focus on improvement. Higher tender acceptance is associated with shorter dwell times (Banker, 2016).
3. Fleet Diversification: Multi-sourcing or establishing contracts with a variety of large providers will strengthen a company's ability to augment capacity, improve service, and obtain superior rates (Costantino & Pellegrino, 2010).

4. Lead-Time Optimization: This involves identifying opportunities within the transportation network to augment lead time and allow carriers more time to plan the use of their equipment. Longer lead times are associated with a reduction in shipping costs and tender rejection rates (Caldwell & Fisher, 2008).
5. Demand Forecasting: Variability in demand forecasting makes it challenging for carriers to consistently meet the needs of their customers. Improvements in forecasting data collection and analysis will enable carriers to better plan their resources and provide better customer service to shippers. Further, clustering together low volume lanes can improve forecasts and carrier planning (Banker, 2016).
6. Network Optimization: This strategy involves reviewing the network footprint and identifying opportunities to lower costs by modifying network nodes to areas with more competitive rates and capacity. Certain areas are more difficult to source consistent shipping providers. For example, of the 48 contiguous states, below are the 5 worst shipping states based on having the least number of outbound loads (ATBS, 2019):
    - Montana, ranked 44^{th}
    - Wyoming, ranked 45^{th}
    - New Hampshire, ranked 46^{th}
    - Vermont, ranked 47^{th}
    - Rhode Island, ranked 48^{th}
7. Private Fleet: The investment in equipment and management of a private fleet may provide savings. This strategy is recommended for stable lanes and shipments and where back-hauls can be filled to limit moving empty space in private trucks (Bane-Herzog, 2019).

4.3 Contracting Phase

Shippers have a wide variety of contracting strategies to consider. These strategies are tailored towards their business needs and constraints. Further, types of trucking contracts and contractual terms can vary based on a host of reasons including geographic and customer contexts. Listed below are strategies for shippers to consider when applicable in their network.

1. Contract Length: Procurement events are recommended at least on an annual basis. This frequency helps shippers avoid having their rates get ‘stale’. Stale rates occur when rate savings disappear over the course of a contract as carrier networks change and service levels diminish. Madkour, from C.H. Robinson, reports that the savings from gains in customer service will disappear within the initial year of a contract (2017).
2. Optimization of Contract Timing: Research has shown that there is a link between the stage of a contract and the level of customer service provided (Madkour, 2017). To improve tender acceptance rates, the contract start dates and length can be strategically timed in line with the spot rate forecast to yield the best results for critical lanes. Further, shippers should consider timing procurement events for when it is good for their business cycle (C.H. Robinson, 2017).
3. Planned Spot: The planned spot option involves reserving a segment of the transportation volume for the spot market. Depending on the region, it is recommended to reserve 5-10% of the volume for this tactic. There is risk associated with this option as it directly exposes the shipper, in part, to the volatile spot rate. Further, this option is internally costly as the shipper must continually arrange shipments with new carriers, which may also have a negative impact on customer service. However, this allows companies to be closely aware

of the activity of the market and to financially benefit from a soft market - when the spot rate drops below the contract rate.

4. Quid Pro Quo Contract: A Quid Pro Quo contract involves a binding contract – different from most other contracts. In this case, the carrier is obligated to carry 100% of the predetermined volume and the shipper is obligated to tender that volume of truckloads every week. If either of these obligations are not fulfilled, financial penalties outlined in the contract shall be paid to the appropriate party. Due to the binding nature of this mechanism, this should be reserved for consistent lanes that have reliable demand forecast. Further, a buffer should be incorporated where, for example, only 80% of the forecasted volume should be placed under the agreement. This option can provide very stable prices and will lead to the best customer service due to the carrier consistency. There will also be auxiliary internal costs with tracking performance and imposing or paying penalties when the contract terms are violated.
5. Index Based Contract: This strategy involves linking the contract rate to a market indicator. The DAT rate may be used or another prominent rate that both parties agree upon. The shipper and carrier will need to agree on how often to update the index (e.g. monthly). This strategy should result in a higher tender acceptance rate than typical contracts because carriers are being compensated when the spot rates increase (Sinha & Thykandi, 2019). Further, shippers are able to benefit when the spot rate declines in a soft market. This option has increased variability as the transportation costs fluctuates with the market which is a concern for annual budget planning. Customer service levels under this arrangement would be high due to carrier consistency and auxiliary costs would be low due to the long-term contract agreement.

6. Hedging the Market: In March 2019, the FreightWaves and DAT launched the trucking freight futures contracts on the Nodal Exchange. This can potentially allow shippers and carriers the ability to decrease their risk exposure to the transportation market. At the time of this paper there was insufficient trading on the exchange for the market stakeholders to fully benefit from a hedging strategy.

The above contracting considerations require planning and processing resources to execute and monitor. The estimated impact on an organization and a contracting team should be incorporated in the decision-making process for a contractual strategy. Further, the strategy should be revisited regularly and evaluated based on predefined metrics.

4.4 Tactical Phase

The unstable nature of the spot rate demands short-term options to mitigate disturbances associated with volatility in the trucking industry. The list below provides short-term measures for shippers to employ under appropriate conditions.

1) Vendor Relationship Maintenance: Resources should focus on improving the value of supplier relationships. A key component is frequent communication with the vendor to express requirements and obtain capacity updates (Bhuvaneswaran, 2019). Related actions include regular senior management meetings with carriers to stress the importance of honoring contracts in order to preserve the current and future business relationship. When appropriate, carriers can be included in strategic planning. Carrier data and insights may prove helpful with network demand planning.
2) Opportunistic Spot: This tactic involves entering typical annual contracts while reserving the option to select the spot rate when it is below the contract rate. Opportunistic spot allows a shipper to obtain the lowest transportation cost at any given time. The total cost

needs to be considered as there are costs associated with brokering freight auction tenders and potential changes in service levels. Despite the cost advantages, many shippers are reluctant to employ this strategy due to a concern of carrier reciprocity – the idea that the carrier will penalize the shipper for ignoring the contractual agreement. However, Acocella, Caplice, and Sheffi (2019) found that carriers behave like 'goldfish' with short memories and tend not to seek retribution based on shippers' tenders from a previous period.

3) Mini-Bids: Mini-bidding involves soliciting for a fraction of the total transportation need as opposed to the entire amount (ComFreight, 2019). Mini-bids are often shorter contracts (3-6 months) and can provide several advantages to shippers. They permit a shipper to test out a new carrier or to allocate new business to alternative carriers in a region to measure performance amongst routing guide options. Mini-bids can also lock in preferred rates or conditions ahead of forecast market volatility. Depending on the anticipated direction of the market, either Quid Pro Quo or Index Based contracts could be implemented. Mini-bids increase the number of contract arrangements and require resources to set-up and manage.

4) Market Accessorial: A Market Accessorial is a short-term premium paid on top of the existing contract rate. There is a strong correlation between the Spot Rate / Contract Rate ratio and the tender acceptance rate of shippers. This option leverages that relationship to offset the costs associated with a lower tender acceptance rate by increasing the contract rate and altering the ratio. The Market Accessorial would be offered to select carrier(s) in a geographic area that is experiencing particularly low tender acceptance rates. The location and timing of the Market Accessorial needs to be carefully analyzed to ensure that

it will achieve cost savings. The evaluation criteria of the Market Accessorial is explained in Section 5.

This section outlined our Tactical Playbook of contractual elements for shippers to consider during contract planning, design, and implementation. The needs of companies vary throughout their networks and change over time. Likewise, the landscape of the trucking industry is constantly in flux with different companies, new regulations, changing capacities, and rates. In Section 5.2 we discuss the application of these measures under different market conditions.

5 Results and Discussion

Our project focused on two key components: forecasting the national spot rate and developing a playbook to help companies manage their truckload transportation operations. The spot rate was forecasted using the VAR and ARIMA models explained in Section 3. The machine learning multivariate nature of the VAR model yields accurate long-term results and the univariate moving-average characteristics of the ARIMA model are most appropriate for short-term forecasts. Combined, the two models provide an accurate prediction of the spot rate over the coming year while accounting for unexpected events disturbing the trucking market.

Following the forecasting model results, the playbook will be discussed in Section 5.2. The playbook provides guidance and options for companies to consider based on the predicted spot rate. Recommendations are provided in line with varied market conditions and an instructive example walks through a hypothetical scenario.

5.1 VAR and ARIMA Forecasts

We developed an alternative approach applying machine learning to a unique set of variables through VAR and ARIMA(4,1,2) models. This section provides the testing results of these models and their future forecasts.

The models and their testing sets are evaluated on accuracy, through the mean absolute percent error (MAPE), and bias, through mean error. Table 10 contains the results of both the VAR and ARIMA forecasts for January, February, and March of 2020.

Table 10: Forecast Results of Project Models

Model	Measurement	Jan 2020	Feb 2020	March 2020
VAR	MAPE	6.81%	4.1%	2.96%
	Mean Error	-0.11%	-0.06%	-0.04%
ARIMA	MAPE	3.87	5.38%	4.2%
	Mean Error	-0.06%	-0.08%	-0.06%

The VAR and ARIMA models both exhibit minimal negative bias through the mean error test statistic and significant accuracy through the MAPE. Over this range period the average MAPE for the VAR and ARIMA models are 4.62% and 4.48% respectively.

The forecasts in Table 10 used machine learning to train on data from January 2009 to December 2019 for the 2020 predictions. To further evaluate the models, the training and testing sets were applied to larger historical ranges for both the VAR and ARIMA projections. Table 11 displays the results for the VAR model tested at 6-month intervals over a 6-year period from April 2014 to March 2020.

Table 11: VAR Forecast Tests

Training Set		Testing Set		Mean Error	MAPE
Start Date	End Date	Start Date	End Date		
Jan-09	Mar-19	Apr-19	Mar-20	0.02	1.96%
Jan-09	Sep-18	Oct-18	Sep-19	-0.14	8.87%
Jan-09	Mar-18	Apr-18	Mar-19	-0.04	4.35%
Jan-09	Sep-17	Oct-17	Sep-18	0.03	3.39%
Jan-09	Mar-17	Apr-17	Mar-18	0.19	10.66%
Jan-09	Sep-16	Oct-16	Sep-17	-0.07	4.93%
Jan-09	Mar-16	Apr-16	Mar-17	0.02	1.99%
Jan-09	Sep-15	Oct-15	Sep-16	-0.13	9.50%
Jan-09	Mar-15	Apr-15	Mar-16	-0.26	17.45%
Jan-09	Sep-14	Oct-14	Sep-15	-0.07	5.84%
Jan-09	Mar-14	Apr-14	Mar-15	0.01	3.29%

The MAPEs of the forecasts in Table 11 fluctuated from a minimum of 1.96% to a maximum of 17.45%, with a mean of 6.57%. The mean errors throughout the forecasts consistently showed minimal evidence of bias in the model with a mean of -0.04.

Table 12 displays the results for the ARIMA model tested over 3-month ranges from February 2019 to March 2020.

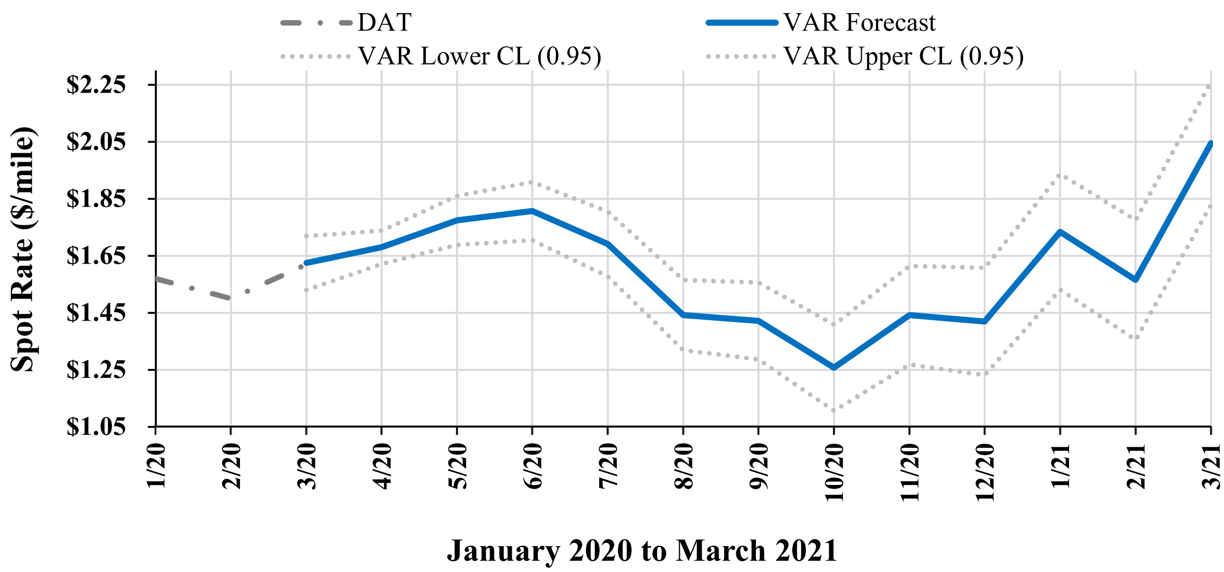
Table 12: ARIMA Forecast Tests

Training Set		**Testing Set**		**Mean Error**	**MAPE**
Start Date	End Date	Start Date	End Date		
Jan-09	Dec-19	Jan-20	Mar-20	-0.06	4.20%
Jan-09	Nov-19	Dec-19	Feb-20	0.00	2.22%
Jan-09	Oct-19	Nov-19	Jan-20	0.08	5.23%
Jan-09	Sep-19	Oct-19	Dec-19	0.02	2.96%
Jan-09	Aug-19	Sep-19	Nov-19	-0.03	1.88%
Jan-09	Jul-19	Aug-19	Oct-19	-0.01	1.35%
Jan-09	Jun-19	Jul-19	Sep-19	-0.06	3.57%
Jan-09	May-19	Jun-19	Aug-19	0.05	3.07%
Jan-09	Apr-19	May-19	Jul-19	0.04	2.32%
Jan-09	Mar-19	Apr-19	Jun-19	-0.01	2.33%
Jan-09	Feb-19	Mar-19	May-19	-0.12	8.31%
Jan-09	Jan-19	Feb-19	Apr-19	-0.12	7.76%

The MAPEs of the forecasts in Table 12 fluctuated from a minimum of 1.35% to a maximum of 8.31%, with a mean of 3.77%. The reduced variance in the forecast accuracy of the ARIMA model compared to the VAR model can be attributable to the shorter forecast horizon of the ARIMA model.

Figure 7 depicts the 12-month VAR forecast using the complete data set (January to March 2020) to train the machine learning model.

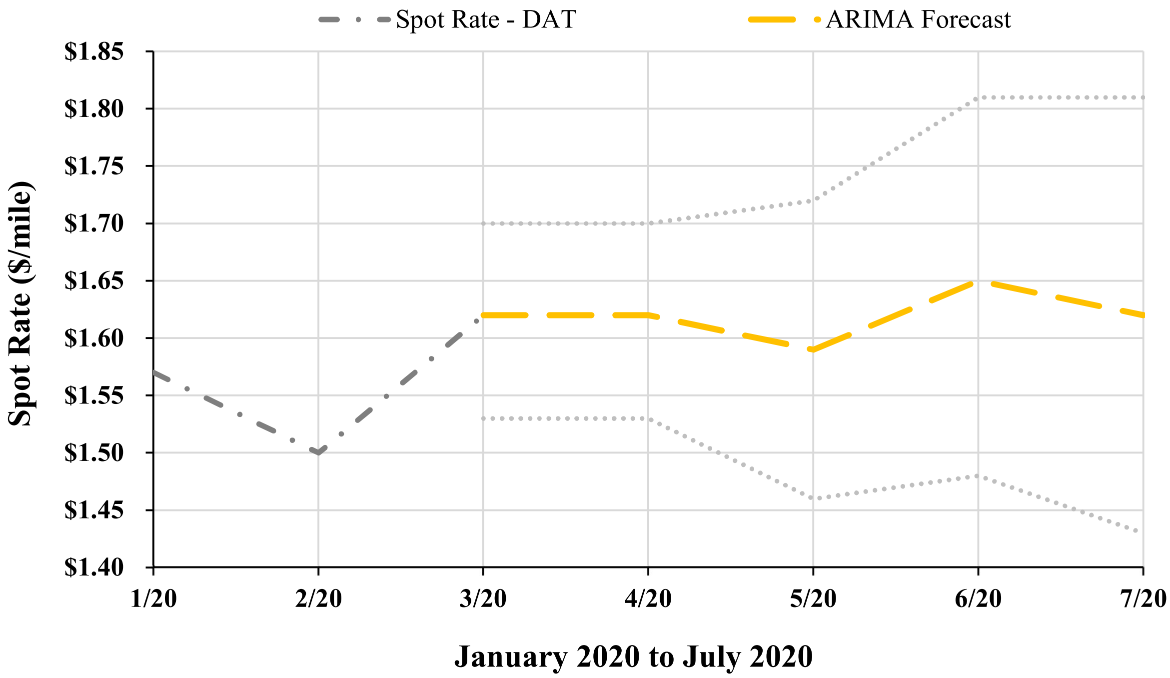
Figure 7: VAR Monthly National Spot Rate Forecast



The VAR model predicts an initial upward movement before significantly declining to a local minimum of $1.26 in October 2020. The forecast indicates preferential spot rates for the shipper through the summer before the market corrects and rates increase through the beginning of 2021.

As discussed in the methodology section, the data for the VAR model has an up to 2-month lag. The ARIMA univariate model was developed to bridge this time window and capture any recent events that would impact the trucking market and potentially indicate a directional shift in the VAR model. In Figure 8, a forecast is displayed for April 2020 to July 2020.

Figure 8: ARIMA Monthly National Spot Rate Forecast



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The ARIMA forecast depicts a different trajectory than the VAR forecast for the coming 3-months. The ARIMA model indicates a local minimum of $1.59 in May 2020 before trending upward through June 2020.

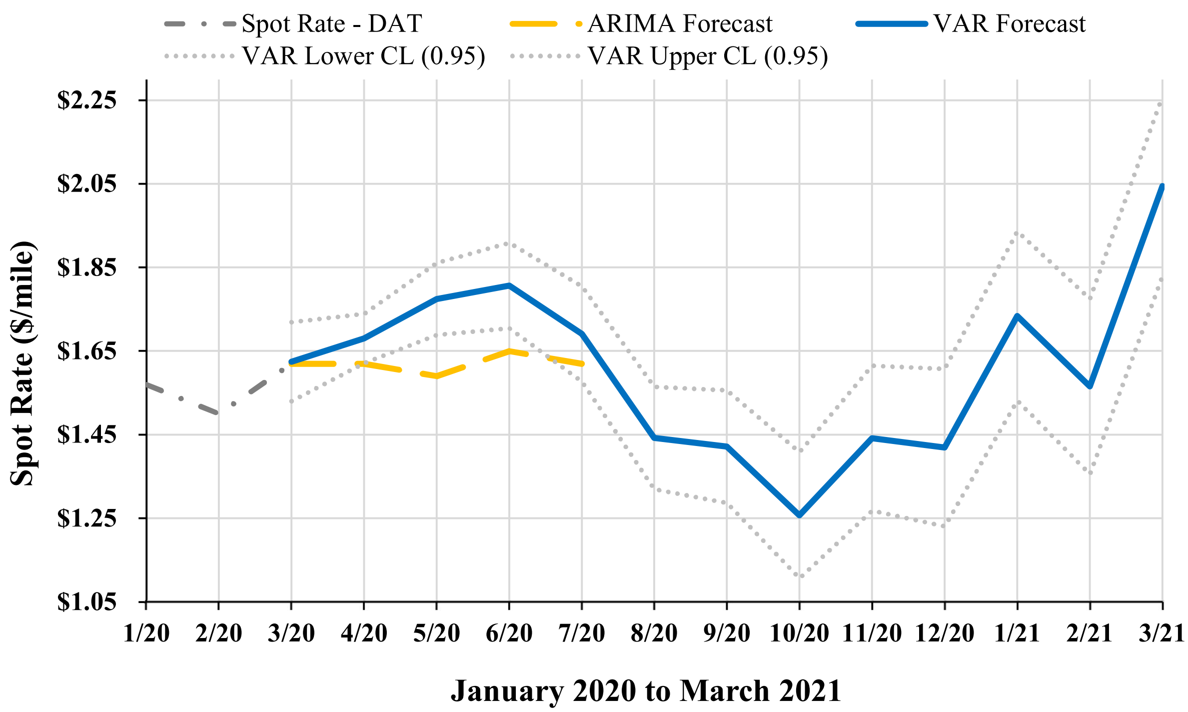
Table 13 compares the ARIMA and VAR projections over the coming 6 months and shows the percent difference between the forecasts.

Table 13: VAR and ARIMA Model Spot Rate Comparison

Model	Apr ‘20	May ‘20	Jun ‘20	Jul ‘20	Aug ‘20	Sep ‘20
VAR	1.68	1.77	1.81	1.69	1.44	1.42
ARIMA	1.60	1.56	1.62	1.59	1.55	1.60
Difference (%)	5%	13%	12%	6%	7%	11%

Figure 9 combines the spot rate forecasts for the VAR and ARIMA models.

Figure 9: ARIMA and VAR Monthly National Spot Rate Forecasts



In Figure 9 we can clearly see the difference between the VAR and ARIMA forecasts for the coming months. Due to the superior reactivity of the ARIMA method to model in the short-term and the ability of VAR to achieve long-term accuracy, both models should be used in unison. The tandem model approach provides a better picture of future market conditions than a single model and permits tactical action based on anticipated rates. In Section 5.2, we further explore how and when to apply the options in our Technical Playbook.

5.2 Tactical Playbook

The playbook was developed to inform tactical actions and accompany the spot rate forecasts. The guide defined in Section 4 describes areas to focus on during the planning phase, items to consider during the contracting phase, and actions reserved for the tactical phase. Assuming planning phase elements have been addressed, below we match contractual factors to circumstances and then discuss the appropriate conditions for tactical actions.

5.2.1 Contract Phase

Establishing contracts with carriers is attractive due to the expected customer service levels and relative stability in rates. On average 20% of tenders will end up getting rejected by carriers (Kim, 2013), but most truckloads will be shipped at contract rates. Section 4 highlighted C.H. Robinson's point against letting contracts get 'stale' and how varied contract length can be used as a tool to garner higher service levels and rate consistency. In markets with a large supply of carriers, shorter contracts can be used as carrier performance is typically at its peak at the beginning of a contract and savings will deteriorate over time. This contract strategy can benefit from exploring new carriers and avoiding being locked into higher rates when the market is expected to soften, and rates will decline. Costs associated include the increased strain on the contracting department as well as poorer customer service due to changing carriers.

The timing of contracts can also mitigate exposure to higher costs. Staggering procurement events at different times of the year will stabilize the overall rate by diversifying the contracting portfolio across varied market conditions. Further, launching procurement events on a rolling cycle can spread out pressure placed on a shipper's contracting team and be used to avoid or even take advantage of seasonal anomalies or forecasted spikes. For example, the rolling contract structure could be optimally aligned with predicted market conditions by setting the start date, end date, and duration of contracts around the forecasted peaks and valleys.

Two beneficial types of contracts to consider are Quid Pro Quo and Index Based. The binding nature of the Quid Pro Quo contract carries an inherent cost and risk for the shipper, although it also offers protection against higher costs. Quid Pro Quo arrangements are ideal when the trucking market is expected to tighten, and spot rates will increase. In this context the costs related to fulfilling minimum volume requirements will be outweighed by the savings of a stable contract rate amidst a rising spot rate.

The Index Based contract offers the shipper stability in being able to consistently source their capacity needs. This contract also allows shippers to benefit financially when a market softens, and the spot rate decreases. Due to its fluctuating nature, Index Based contracts do lead to high variability in transportation costs and can impact annual budget planning. The Quid Pro Quo, the Index Based contract, or a combination of the two require significant resources to set-up, track, and manage.

Another measure is the Planned Spot strategy. Dedicating trucking volume to the spot market offers flexibility, risk, and reward. Shippers with non-contracted freight could wait for optimal market conditions to implement a contract or evaluate new carrier options. Further, Planned Spot volume is subject to the volatility of the spot market and has costs associated with increased awards and the instability of varied carriers. Although, when the trucking market is expected to soften, the Planned Spot option would allow shippers to fully realize cost savings with lower spot rates.

At the time of writing this paper regular activity has not yet been achieved for freight futures trading on the Nodal Exchange. Nevertheless, the possibility of hedging the trucking market can be a powerful strategy for shippers to protect themselves against a volatile spot market. Shippers trading freight futures should also adopt the Opportunistic Spot strategy to achieve rate stability. For example, shippers expecting the market to tighten could buy futures at a low price to sell when the market increases in order to offset the costs associated with the rising spot rate. Further, if the market unexpectedly softened, the shipper could gain savings on the spot market to offset their futures position. The costs associated with this tactic relate to resources dedicated to tracking the futures market and engaging in the Opportunistic Spot approach. Freight futures trading is in its infancy but has potential and should be followed.

The strategic contracting options noted above provide shippers with options across market conditions. The forecasting of the spot rate can guide when to consider which option. The direct and indirect costs discussed should be included when evaluating and comparing strategies. Further, network characteristics may lead to market inconsistencies across regions and the implementation of multiple contract types over the same period.

Table 14 summarizes the key characteristics of the contract phase strategies and their appropriate market condition.

Table 14: Contract Phase Options

	Con. Timing & Duration	Planned Spot	Quid Pro Quo	Index-Based Contract	Market Hedging
Market Conditions	Spot to decline	Spot to decline	Spot to increase	Low supply	Volatile
Target Lanes	High supply lanes	Noncritical lanes	Most consistent lanes	Consistent lanes	N/A
Time Frame	Varied	< 1 year	2+ year	2+ years	Continuous
Transport Costs	Variable	Volatile	Highly stable	Less variable than spot market	Stabilized with hedging
Internal Costs	High	Extremely high	Medium	Low	High
Risk Level	High	Extremely high	Medium	Low	Low
Service Level	Medium	Low	High	High	N/A
Additional Factors	Budget difficulties	Provides market information	Institute security margin	Budget difficulties	Requires active trading

5.2.2 Tactical Phase

There are several tactical actions that shippers can take to improve their situation amidst changing trucking market conditions. The tactical phase guidance relates to options for shippers throughout the duration of carrier contracts. The market condition and the anticipated level of change in the market dictate the action and magnitude of the intervention.

Building close relationships with carriers allows shippers greater leverage during market disturbances. Extending those relationships across multiple work streams can deepen that leverage. For example, joint projects involving data analytics, improving customer service, and enhancing networks can create an interdependency and stronger adherence to contractual terms. With limited resources, shippers' focus on vendor relationship maintenance and engagement should prioritize vital carriers. Further, when spot rate increases are forecasted, additional resources should be dedicated to those carriers.

As noted earlier, the nonbinding nature of trucking contracts leads to carriers selling their assets to the spot market when rates are relatively high. When market conditions are reversed, shippers are incented to operate in the same manner. To offset the expected losses during a tight market, shippers should capture available savings during a soft market through the spot rate that is below their contract rate. The Opportunistic Spot tactic is recommended for lanes with high trucking capacity where competition will further lower spot rates and alternative carrier options are readily available. The total cost of the Opportunistic Spot should consider resources associated with brokering freight auction tenders and potential changes to customer service levels.

The Mini-Bid tactic can be applied regardless of the anticipated direction of the market. When a rise in the spot rate is forecasted, a Mini-Bid can be used to lock in preferred rates and the Quid Pro Quo option can be applied to lanes with consistent volume. When a decline is forecasted, a Mini-Bid can establish an Index Based contract to benefit from lower spot rates while preserving customer service levels. The forecasting model provides guidance for the Mini-Bid contract timing and duration. Mini-Bids increase the frequency of procurement events and incur greater internal costs accordingly.

The Market Accessorial is related to the Mini-Bid tactic as it also looks to redefine contractual terms considering anticipated changes in the trucking market. However, Market Accessorial involves modifying existing contracts. The following section discusses the Market Accessorial tactic in detail.

5.2.3 Market Accessorial Equation and Worksheet

A Market Accessorial can be defined as a short-term premium extended to a contracted carrier. This tactic can be advantageous for shippers when the contract and spot rate form certain conditions. The successful implementation of a Market Accessorial is dependent on the Spot Premium Ratio, defined as the spot rate divided by the contract rate. In analyzing data of a large domestic shipper, our research found a strong correlation between the Tender Acceptance Rate (TAR) and the Spot Rate Premium. With TAR, spot and contract rates at the lane or regional level, companies can formulate a regression equation tailored to their network. Equation 4 shows the regression equation defining this relationship and the testing equation for determining when to apply a Market Accessorial:

Equation 4: Market Accessorial Validation

Linear Regression Equation

$$TAR = a - b * SPR$$

Test Equation

$$\frac{\Delta TAR * (S-C)}{TAR + \Delta TAR} > MA$$

where

a = The intercept
b = The coefficient of the Spot Rate Premium
SPR = The Spot Rate Premium derived from the spot rate divided by the contract rate
S = Freight Auction rate per mile
C = Contract rate per mile
TAR = Percent volume of tenders accepted at the contract rate
ΔTAR = Difference between original TAR and the new TAR with the MA applied
MA = Market Accessorial

The Test Equation calculates whether a Market Accessorial can yield transportation savings when applied to a specific lane or region. These opportunities are most often realized when the TAR is below average and the slope of the TAR (ΔTAR) is steep, permitting a significant increase in the TAR when the Market Accessorial is applied.

A Market Accessorial Worksheet (Appendix B) was developed to assist companies with maximizing these opportunities. The worksheet data points include origin zip code, destination zip code, carrier, linehaul length, and date. This information combined with the company's regression equation will identify the appropriate conditions for a Market Accessorial as well as the optimal accessorial magnitude and duration. The worksheet calculates the Net Present Value (NPV) of one-month, two-month, and three-month accessorial durations to inform the selection of the most cost-effective time horizon. Further, the worksheet applies a customer service multiplier to the NPV to account for the impact that higher tender acceptance rates have on customer service levels.

The playbook contracting strategies and tactical actions discussed in Section 5.2 provide shippers with a range of options across varied market conditions. The options need to be carefully measured to capture all related costs and, when resources allow, can be used in conjunction with one another. Section 5.3 provides a scenario applying the Tactical Playbook.

5.3 Illustrative

This scenario involves addressing critical and consistent lanes that historically experience poor tender acceptance rates (TAR) and whose rejected tenders are subject to higher costs on the spot market. Various carriers have been contracted in the past on these lanes and the TAR continues to struggle. In order to improve performance on these important lanes, we first must identify the root causes of the problem.

5.3.1 Planning Phase

We start by looking at our internal systems for outliers in the network that may be impacting performance on the lanes. We analyze data metrics associated with Dwell Time, Lead Time, and Demand Forecasting. Metrics in each domain are reviewed and measured against lanes of similar characteristics as well as the network. All anomalies undergo deeper inspection to identify the areas to address. Further, our internal review is accompanied by information gathered from the carrier on why it is challenging to fulfill requirements on the lanes and their related recommendations.

The research identified characteristics of the lanes that are leading to the lower tender acceptance rates. Interventions are planned to correct areas where possible, but some cannot be improved due to operational needs (e.g. lead times).

At this point carrier options are revisited. Carriers not previously considered for this lane or region are added to the list of potential carriers. Further, carrier selection is modified to concentrate on the characteristics of the lanes and those that demonstrated strength in these areas.

5.3.2 Contracting Phase

The carrier X, that traditionally operates in another area of the network, was identified for these lanes. Further, the market forecast indicates that the spot rates are going to increase significantly over the next 6 months before correcting to current levels. The contract team also has available resources to manage additional responsibilities.

Under the conditions above, a short-term 6-month contract is awarded to carrier X, expanding their role in the network. The short-term duration covers the expected spike in the spot rate and allows us to test out carrier X on their new lanes. We proposed a Quid Pro Quo based on the high volume and consistent demand of the lane. However, we went with a traditional contract since were unable to agree on the penalty structure for failing to either meet the volume or TAR levels.

5.3.3 Tactical Phase

A kick-off meeting is held with carrier X involving senior management to express the importance of these lanes and this venture. Managers from the shipper and carrier X agree to convene bi-weekly to review the performance of carrier X. Further, a representative from carrier X is provided a working station at the shipper's location to facilitate trouble shooting issues that develop in real-time.

Several months into the contract the spot rate rose to 39% higher than the contract rate. We suddenly saw that tender acceptance rates dropped off and our total transportation costs increased. Carrier X was candid about selling their assets to the spot market to improve their bottom-line but were open to finding a solution and preserving the business relationship.

We proposed a Market Accessorial for the remainder of the contract. The original contract rate was $1.40 and the current spot rates were $1.95. In addition, the TAR decreased from 100% to 70% after the spike in spot rates. Based on our worksheet we calculated an accessorial amount of $0.15 to add to the current contract rate that would yield a reduction in our total cost. The $0.15 Market Accessorial improved the TAR with carrier X from 70% to 98%. The Market Accessorial achieved $11,250 in savings per 1,000 truckloads over the remaining 3 months of the contract. With a discount rate of 5%, the net present value of the Market Accessorial investment was $10,212 per 1,000 truckloads. Table 15 covers the details of the calculation. The complete Market Accessorial is available in Appendix B.

Table 15: Market Accessorial Calculations

Variable	Inputs
Contract Price (Cost Prime), Cp	$1.40
Forecast of Spot Rate (Cost Auction), Ca, Month T+1	$1.95
Forecast of Spot Rate (Cost Auction), Ca, Month T+2	$1.95
Forecast of Spot Rate (Cost Auction), Ca, Month T+3	$1.95
Origin Region	Southeast
Destination Region	Northeast
Miles between Destination and Origin	250
Quantity of Truck Loads per Month	1000
Freight Type	Customer
Carrier	Carrier X
Month	April
Year	2020
Discount Rate	5%
Customer Service Level (CSL) Multiplier	$1.00

Variable	Month 1	Month 2	Month 3
Market Accessorial Premium	$0.15	$0.15	$0.15
Spot (FA) / Contract Price Ratio	1.39	1.39	1.39
Expected Volume % at Contract Price, Vp	70%	70%	70%
Expected Volume % at Spot (FA) Price, Va	30%	30%	30%
Market Accessorial + Contract Cost	$1.55	$1.55	$1.55
Spot / Market Accessorial + Contract Ratio	1.26	1.26	1.26
Exp. Volume % at MA + Contract Price, Vp1	100%	100%	100%
Exp. Volume % at Spot (FA) Price, Va1	0%	0%	0%
Total Expected Cost	$391,250	$391,250	$391,250
Projected Total Cost with Market Accessorial	$387,500	$387,500	$387,500
Projected Savings with Market Accessorial	$3,750	$3,750	$3,750
Present Value of Monthly Savings	$3,571	$3,401	$3,239
Net Present Value of Total Savings	$10,212		

6 Conclusion

The transportation of goods across the US is predominantly managed by the trucking industry (McNally, 2019). The costs associated with trucking these goods are a major expense for companies. In fact, *Logistics & Management* reported that most of their survey respondents spent more than 11% of their sales in 2018 on domestic transportation (L&M, 2018). Further, as explained above, trucking costs are highly volatile and as a result companies are unable to accurately predict their annual transportation budgets.

This paper discusses our machine learning vector autoregression multivariate model and our ARIMA univariate model to forecast transportation costs. The VAR model forecasts 12 future monthly observations of the US dry van spot rate with significant accuracy and minimal bias. The ARIMA model complements the initial 3-months of the VAR model to capture any immediate disruptions in the trucking market. The forecast model accuracy and comprehensive outlook enhance the value of the guide developed.

The Tactical Playbook provides context specific options for shippers to best navigate the volatile trucking industry. Playbook interventions target contractual arrangements and relationships with carriers to minimize tender rejections and associated customer service and cost repercussions. The models developed will continue to gather new data on a monthly basis to measure its accuracy and extend the rolling forecast for additional periods. Further, the effectiveness of the tactical interventions will be recorded and examined based on their success.

The work described in this paper centers on the national spot rate for dry van trucks. The Tactical Playbook is tailored to dry van truckload transportation; however, the forecasting model and methodology can be adapted for other types of vehicles (e.g. flatbeds, tankers, and reefer trucks) or other transportation modalities (e.g. rail, maritime, and air transport). Further, our nationally focused project can be narrowed to specific geographic areas. With disaggregated data, our process could help explain variance found in regional and lane spot rates.

We hope our forecasting model and Tactical Playbook will assist shippers design, plan, and manage their transportation needs to deliver strong customer service and control costs through market volatility.

Appendix A: Econometric Test Statistics

Table A.1: Ordinary Least Squares of VAR model variables

OLS, using observations 2009:01-2020:03 (T = 135), Dependent variable: SPOT

Variable	Coefficient	Std. Error	t-ratio	p-value
const	−2.35127	0.518997	−4.530	<0.0001***
Load_to_Truck_Ratio	0.117898	0.0123523	9.545	<0.0001***
Export_Price_Index_Crop_Prod	−6.48251e-06	1.10823e-06	−5.849	<0.0001***
Composite_Leading_Ind	0.000377272	5.51290e-05	6.843	<0.0001***
Producer_Price_Index	−0.0127972	0.00276784	−4.624	<0.0001***

Mean dependent var	1.438148	S.D. dependent var	0.201821
Sum squared resid	1.613137	S.E. of regression	0.111395
R-squared	0.704447	Adjusted R-squared	0.695353
F(4, 130)	77.46348	P-value(F)	1.83e-33
Log-likelihood	107.2721	Akaike criterion	−204.5443
Schwarz criterion	−190.0179	Hannan-Quinn	−198.6411
rho	0.860154	Durbin-Watson	0.264423

Table A.2: VAR model equations, P-Values, Portmanteau test, and Durbin-Watson tests

VAR system, lag order 5, OLS estimates, observations 2009:06-2020:03 (T = 130)
Log-likelihood = -1508.4887, Determinant of covariance matrix = 8251.3594
AIC = 26.1306, BIC = 30.3216, HQC = 27.8335
Portmanteau test: LB(32) = 725.501, df = 675 [0.0870]

Equation 1: SPOT

Mean dependent var	1.449615	S.D. dependent var	0.196774
Sum squared resid	0.114052	S.E. of regression	0.035209
R-squared	0.977166	Adjusted R-squared	0.967983
F(37, 92)	106.4090	P-value(F)	4.04e-61
rho	−0.033860	Durbin-Watson	2.064729

Equation 2: Load_to_Truck_Ratio

Mean dependent var	2.333615	S.D. dependent var	0.982556
Sum squared resid	20.24301	S.E. of regression	0.469076
R-squared	0.837456	Adjusted R-squared	0.772085
F(37, 92)	12.81082	P-value(F)	4.70e-23
rho	−0.002913	Durbin-Watson	2.001455

Equation 3: Export_Price_Index_Crop_Prod

Mean dependent var	32271.81	S.D. dependent var	10012.05
Sum squared resid	5.84e+08	S.E. of regression	2519.896
R-squared	0.954823	Adjusted R-squared	0.936654
F(37, 92)	52.55234	P-value(F)	1.16e-47
rho	−0.029091	Durbin-Watson	2.045625

Equation 4: Composite_Leading_Ind			
Mean dependent var	9955.769	S.D. dependent var	166.5226
Sum squared resid	8286.371	S.E. of regression	9.490482
R-squared	0.997684	Adjusted R-squared	0.996752
F(37, 92)	1070.904	P-value(F)	1.1e-106
rho	0.200048	Durbin-Watson	1.524337

Equation 5: Producer_Price_Index			
Mean dependent var	1.335615	S.D. dependent var	4.023242
Sum squared resid	101.9135	S.E. of regression	1.052500
R-squared	0.951192	Adjusted R-squared	0.931563
F(37, 92)	48.45789	P-value(F)	3.82e-46
rho	−0.028316	Durbin-Watson	2.052095

Table A.3: VAR Lag Selection

VAR system, maximum lag order 12
The asterisks below indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags	loglik	p(LR)	AIC	BIC	HQC
1	-1608.24517		27.613743	29.671438	28.449574
2	-1544.35221	0.00000	26.981337	29.610615*	28.049343
3	-1519.19484	0.00195	26.978778	30.179638	28.278959
4	-1465.70444	0.00000	26.515519	30.287962	28.047876
5	-1410.25985	0.00000	26.020485	30.364510	27.785017*
6	-1384.36704	0.00128	26.005968	30.921575	28.002675
7	-1364.07234	0.02534	26.082477	31.569666	28.311359
8	-1343.49825	0.02215	26.154443	32.213214	28.615501
9	-1318.60111	0.00226	26.156116	32.786469	28.849348
10	-1293.25417	0.00175	26.150474	33.352410	29.075882
11	-1252.95201	0.00000	25.901659*	33.675176	29.059242
12	-1238.26833	0.24885	26.069404	34.414504	29.459162

Table A.4: VAR Autoregressive Conditional Heteroscedasticity (ARCH) Test

Test for ARCH of order up to 5			
	LM	**df**	**p-value**
lag 1	291.390	225	0.0019
lag 2	524.251	450	0.0088
lag 3	750.662	675	0.0225
lag 4	983.604	900	0.0269
lag 5	1204.315	1125	0.0496

Table A.5: VAR Normality of Residuals Test – Eigenvalues

Eigenvalues of C:
1) 0.162148; 2) 0.726461; 3) 0.971988; 4) 1.23102; 5) 1.90838

Residual correlation matrix, C (5 x 5)

1.0000	0.79580	-0.16805	0.13129	-0.16478
0.79580	1.0000	-0.010892	0.26111	0.046497
-0.16805	-0.010892	1.0000	-0.063017	0.15713
0.13129	0.26111	-0.063017	1.0000	0.15174
-0.16478	0.046497	0.15713	0.15174	1.0000

Table A.6: VAR Augmented Dickey-Fuller and Engle-Granger Tests

Step 1: testing for a unit root in SPOT
Augmented Dickey-Fuller test for SPOT
including 5 lags of (1-L)SPOT
sample size 129
unit-root null hypothesis: a = 1
 test with constant plus seasonal dummies
 model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
 estimated value of (a - 1): -0.0385222
 test statistic: tau_c(1) = -2.09339
 asymptotic p-value 0.2475
 1st-order autocorrelation coeff. for e: 0.000
 lagged differences: F(5, 111) = 2.586 [0.0298]

Step 2: testing for a unit root in Load_to_Truck_Ratio
Augmented Dickey-Fuller test for Load_to_Truck_Ratio
including 5 lags of (1-L)Load_to_Truck_Ratio
sample size 129
unit-root null hypothesis: a = 1
 test with constant plus seasonal dummies
 model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
 estimated value of (a - 1): -0.1445
 test statistic: tau_c(1) = -2.80384
 asymptotic p-value 0.05768
 1st-order autocorrelation coeff. for e: -0.007
 lagged differences: F(5, 111) = 1.653 [0.1521]

Step 3: testing for a unit root in Export_Price_Index_Crop_Prod
Augmented Dickey-Fuller test for Export_Price_Index_Crop_Prod
including 5 lags of (1-L)Export_Price_Index_Crop_Prod
sample size 129
unit-root null hypothesis: a = 1
 test with constant plus seasonal dummies
 model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
 estimated value of (a - 1): -0.0409878
 test statistic: tau_c(1) = -1.65111
 asymptotic p-value 0.4563
 1st-order autocorrelation coeff. for e: 0.014
 lagged differences: F(5, 111) = 0.574 [0.7200]

Step 4: testing for a unit root in Composite_Leading_Ind
Augmented Dickey-Fuller test for Composite_Leading_Ind

including 5 lags of (1-L)Composite_Leading_Ind
sample size 129
unit-root null hypothesis: a = 1
  test with constant plus seasonal dummies
  model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.0110522
  test statistic: tau_c(1) = -1.82053
  asymptotic p-value 0.3709
  1st-order autocorrelation coeff. for e: 0.053
  lagged differences: F(5, 111) = 199.372 [0.0000]

Step 5: testing for a unit root in Producer_Price_Index
Augmented Dickey-Fuller test for Producer_Price_Index
including 5 lags of (1-L)Producer_Price_Index
sample size 129
unit-root null hypothesis: a = 1
  test with constant plus seasonal dummies
  model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.0782957
  test statistic: tau_c(1) = -2.94212
  asymptotic p-value 0.04066
  1st-order autocorrelation coeff. for e: 0.002
  lagged differences: F(5, 111) = 4.860 [0.0005]

Step 6: cointegrating regression
Cointegrating regression -
OLS, using observations 2009:01-2020:03 (T = 135)
Dependent variable: SPOT

	Coefficient	**Std. error**	**t-ratio**	**p-value**
const	−2.20864	0.546041	−4.045	9.34e-05 ***
Load_to_Truck_Ra~	0.123384	0.0135815	9.085	2.75e-015 ***
Export_Price_Ind~	−6.24436e-06	1.16019e-06	−5.382	3.75e-07 ***
Composite_Leadin~	0.000360945	5.82075e-05	6.201	8.39e-09 ***
Producer_Price_I~	−0.0132821	0.00288550	−4.603	1.05e-05 ***

Mean dependent var	1.438148	S.D. dependent var	0.201821
Sum squared resid	1.568585	S.E. of regression	0.114810
R-squared	0.712610	Adjusted R-squared	0.676384
Log-likelihood	109.1626	Akaike criterion	−186.3252
Schwarz criterion	−139.8408	Hannan-Quinn	−167.4353
rho	0.880207	Durbin-Watson	0.228963

Step 7: testing for a unit root in uhat
Augmented Dickey-Fuller test for uhat
including 5 lags of (1-L)uhat
sample size 129
unit-root null hypothesis: a = 1
  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e

estimated value of (a - 1): -0.125734
test statistic: tau_c(5) = -2.72694
asymptotic p-value 0.7232
1st-order autocorrelation coeff. for e: -0.026
lagged differences: F(5, 123) = 2.453 [0.0371]

Table A.7: ARIMA(4,1,2) Model

ARIMA, using observations 2009:02-2020:03 (T = 134)
Dependent variable: (1-L) SPOT, Standard errors based on Outer Products matrix

	Coefficient	Std. Error	z	p-value
const	0.00327870	0.00397687	0.8244	0.4097
phi_1	−0.702421	0.106961	−6.567	<0.0001***
phi_2	−0.893053	0.114655	−7.789	<0.0001***
phi_3	0.104084	0.109195	0.9532	0.3405
phi_4	−0.179001	0.0990239	−1.808	0.0707*
theta_1	0.913733	0.0748842	12.20	<0.0001***
theta_2	0.912442	0.0715517	12.75	<0.0001***

Mean dependent var	0.003433	S.D. dependent var	0.052071
Mean of innovations	0.000056	S.D. of innovations	0.043454
R-squared	0.953730	Adjusted R-squared	0.951922
Log-likelihood	228.6084	Akaike criterion	−441.2168
Schwarz criterion	−418.0341	Hannan-Quinn	−431.7961

	Real	Imaginary	Modulus	Frequency
AR				
Root 1	-0.4967	-0.8720	1.0036	-0.3324
Root 2	-0.4967	0.8720	1.0036	0.3324
Root 3	0.7875	-2.2196	2.3551	-0.1957
Root 4	0.7875	2.2196	2.3551	0.1957
MA				
Root 1	-0.5007	-0.9194	1.0469	-0.3294
Root 2	-0.5007	0.9194	1.0469	0.3294

Table A.8: ARIMA Autocorrelation Ljung-Box Test

Test for autocorrelation up to order 12

Ljung-Box Q' = 13.125, with p-value = P(Chi-square(6) > 13.125) = 0.04109

Table A.9: ARIMA Augmented Dickey-Fuller Test for Spot and 1st Difference of Spot

Augmented Dickey-Fuller (GLS) test for SPOT
testing down from 12 lags, criterion modified AIC
sample size 122
unit-root null hypothesis: a = 1
test with constant
including 12 lags of (1-L)SPOT

model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
estimated value of (a - 1): -0.0154954
test statistic: tau = -0.985243
asymptotic p-value 0.2912
1st-order autocorrelation coeff. for e: -0.001
lagged differences: F(12, 109) = 5.363 [0.0000]

Augmented Dickey-Fuller (GLS) test for d_SPOT
testing down from 12 lags, criterion modified AIC
sample size 128
unit-root null hypothesis: a = 1
test with constant
including 5 lags of (1-L)d_SPOT
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
estimated value of (a - 1): -0.667133
test statistic: tau = -3.21966
asymptotic p-value 0.001255
1st-order autocorrelation coeff. for e: 0.007
lagged differences: F(5, 122) = 8.377 [0.0000]

Table A.10: ARIMA Autoregressive Conditional Heteroscedasticity (ARCH) Test

	Coefficient	**Std. error**	**t-ratio**	**p-value**
alpha(0)	0.00101463	0.000458910	2.211	0.0291 **
alpha(1)	0.133717	0.0961165	1.391	0.1670
alpha(2)	−0.0747073	0.0970184	−0.7700	0.4429
alpha(3)	−0.0179405	0.0962442	−0.1864	0.8525
alpha(4)	0.257523	0.0962078	2.677	0.0086 ***
alpha(5)	0.345860	0.0992221	3.486	0.0007 ***
alpha(6)	−0.0580065	0.104203	−0.5567	0.5789
alpha(7)	0.115907	0.104202	1.112	0.2684
alpha(8)	−0.0516762	0.0993601	−0.5201	0.6041
alpha(9)	0.00766340	0.0962527	0.07962	0.9367
alpha(10)	−0.160582	0.0964522	−1.665	0.0988 *
alpha(11)	0.0113271	0.0974158	0.1163	0.9076
alpha(12)	0.0114934	0.0963621	0.1193	0.9053

Null hypothesis: no ARCH effect is present
Test statistic: LM = 29.7844, with p-value = P(Chi-square(12) > 29.7844) = 0.00300883

Appendix B: Market Accessorial Worksheet

Variable	Inputs
Contract Price (Cost Prime), Cp	$1.40
Forecast of Spot Rate (Cost Auction), Ca, Month T+1	$1.95
Forecast of Spot Rate (Cost Auction), Ca, Month T+2	$1.95
Forecast of Spot Rate (Cost Auction), Ca, Month T+3	$1.95
Origin Region	Southeast
Destination Region	Northeast
Miles between Destination and Origin	250
Quantity of Truck Loads per Month	1000
Freight Type	Customer
Carrier	Carrier X
Month	Jan
Year	2020
Discount Rate	5%
Customer Service Level (CSL) Multiplier	$1.00

$$\frac{\Delta Vp * (Ca-Cp)}{Vp + \Delta Vp} > MA$$

Market Accessorial justified (green) when the Test Equation is greater than MA

Market Accessorial Decision Variable	$0.15
Test Equation for Month 1	$0.24
Test Equation for Month 2	$0.24
Test Equation for Month 3	$0.24

Variable	Month 1	Month 2	Month 3
Market Accessorial Premium	$0.15	$0.15	$0.15
Spot (FA) / Contract Price Ratio	1.39	1.39	1.39
Expected Volume % at Contract Price, Vp	70%	70%	70%
Expected Volume % at Spot (FA) Price, Va	30%	30%	30%
Market Accessorial + Contract Cost	$1.55	$1.55	$1.55
Spot / Market Accessorial + Contract Ratio	1.26	1.26	1.26
Exp. Volume % at MA + Contract Price, Vp1	100%	100%	100%
Exp. Volume % at Spot (FA) Price, Va1	0%	0%	0%
Change in Vp % from ratio	30%	30%	30%
Change in Va % from ratio	-30%	-30%	-30%
Total Expected Cost	$391,250	$391,250	$391,250
Projected Total Cost with Market Accessorial	$387,500	$387,500	$387,500

Projected Savings with Market Accessorial	$3,750	$3,750	$3,750
Present Value of Monthly Savings	$3,571	$3,401	$3,239
Net Present Value of Total Savings	$10,212		

Customer Service Level Multiplier NPV			
Projected Savings with Market Accessorial	$3,780	$3,750	$3,750
Present Value of Monthly Savings	$3,600	$3,401	$3,239
NPV of Total Savings with CSL Multiplier	$10,241		

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