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TITLE:

Forecasting Long Haul Truckload Spot Market Rates

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KEYWORDS:

Truckload, Spot Market, Rate Forecasting, Time Series Forecasting, Linear Regression, Elastic Net Regularization, Concept Drift, Feature Extraction, Explicit Drift Detection

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The objective of this paper is to predict long haul truckload spot market rates for the near future. Short term spot rate forecasts help with making operational decisions, estimating budgets for shippers and cash flow for carriers. First, we check if the weekly spot rates time series is a Random Walk process. In which case a Naïve forecast is better than other auto-regressive time series models and thus we use it as our base forecast. We then use exogenous economic indicators as inputs to a Linear Regression model, fit using Elastic Net Regularization, to check if there are leading indicators for truckload spot rates. An important aspect of the truckload spot market is the periodic cycles of soft (decreasing market rates) and tight (increasing market rates) markets. Such changes in the time series, or concept drift, make old forecasting models irrelevant. We thus use two implicit and one explicit concept drift handling methods to retrain our forecasting models. We create forecasts for 1, 4, 8 and 12 weeks into the future and compare MAPEs of the models to conclude that Naïve model outperforms them in each case. We also discuss how explicit detection of concept drift provides useful information on changes in the market cycle for the stakeholders.

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1. INTRODUCTION

The trucking industry in the USA is a major contributor to the nation's economy. Total US business logistics cost accounted for 8% of the US GDP in 2018, of which 41% was transportation costs by motor carriers (AT Kearney, 2019). The trucking industry consists of shippers and carriers. Shippers are organizations that have goods which need to be transported. Carriers are organizations that provide transportation services. Sometimes, a Broker serves as a middle man connecting shippers and carriers. Ground transportation of freight by motor carriers can further be classified into truckload, less than truckload, and private fleet. Truckload shipments move from a single origin to a single destination and serve one customer per trip. The truck may not be physically full but one shipper pays for the entire vehicle-trip. Less than truckload hauls shipments of less than 10,000 lbs. where multiple customers can be served in each trip, making multiple stops. Private fleet is when shippers own a fleet of trucks. The contribution to the total US business logistics cost in 2018 was \$296.1 billion by truckload, \$71.8 billion by less than truckload, and \$300.9 billion by private fleet (AT Kearney, 2019). The significance of the industry is also reflected in its size. Trucks move over 70% of freight in the US. In addition to being a big market, it is also highly competitive and fragmented. There are more than 1.5 million carriers on record. Very few of those carriers are significantly large in size; 91% of the carriers own less than 6 trucks and 97% have less than 20. (American Trucking Association, 2019). The trucking industry is an important and interesting market to be studied. This paper focuses on the truckload segment of the industry, specifically long haul (≥ 250 miles) shipments within continental USA.

Shippers and carriers typically interact through the procurement process as described by Caplice and Sheffi (2005) and Caplice (2007). There are two phases in this process: strategic and operational. The strategic phase starts with shippers determining their projected demands on specific lanes. They send out a call for bidding to a group of carriers that respond with proposed rates for those lanes at specific volumes. The mutually agreed upon rates are set and are called contract rates. The shipper selects winning carriers for each lane and prepares a routing guide; a list of carriers for a lane in preference order. These contracts are signed for a long term, usually ranging from 1-2 years.

The operational phase occurs when a load is ready to be tendered. At that time the shipper offers the load to its primary carrier (the first carrier on the routing guide). If the carrier accepts, the contract rates are paid. Unlike most other industries, truckload contracts are non-binding in terms of volume for both shippers and carriers. If the carrier doesn't have capacity available or wants to avoid empty backhauls, they can reject the tender without incurring an explicit penalty in most cases. In case of rejection, the shipper contacts the next carrier in the routing guide and so on. However, prices are usually higher as they go down the routing guide, and the process takes up time and resources. Aemireddy and Yuan (2019) found that backup routing guide rates reached up to 15% over the primary carrier rate in 2017-2018. Another option available to the shippers is the spot market. They can hire carriers with available capacity on that lane and pay a one-time price that's decided on a load by load basis. The spot market typically makes up 5-10% of the shipment volume (Caplice, 2007) but increases during a tight market. Spot rates are usually higher and more volatile compared to contract rates and thus more difficult to predict. Some carriers may also reject contract loads expecting to get a better price or volume at the spot market, as Aemireddy and Yuan (2019) note that spot rates were up to 30% higher than primary contract rates in 2017-2018.

Another noteworthy characteristic of the truckload industry is the periodic market cycles. Pickett (2018) described how the truckload industry goes through cycles of tight and soft market which last around 2 years as shown in Figure 1. A tight market is when demand exceeds supply and the rates consequently rise. A tight market is often called the seller's or the carrier's market, as it is favorable to carriers. Carriers increase their capacity to capture the demand. When this increase in capacity materializes, the supply increases. When supply exceeds demand, it becomes a soft market which is favorable to the shippers. Eventually, the demand increases again and we get yet another cycle of tight market. Demand spikes can be caused by factors like holiday season and natural disasters.

An example of such a shift in market was the period between the Fall of 2017 and Fall of 2018. Industry analysists speculated how there was a growth in demand due to economic development and rise of e-commerce, leading to more consumer spending and higher customer expectations. Costello (2017) argued that there was a decrease in supply due to a shortage of drivers as the retiring workforce was not being adequately replaced, and that new laws on hours of service and Electronic Logging Device (ELD) mandates also contributed to a capacity crunch. Carriers shifted their business to lanes with higher returns and re-focused their capacity to the spot market. Furthermore, the US was hit with intense hurricanes during this period. Hurricane Irma and Hurricane Harvey caused capacity to shift to disaster areas leading to scarce services elsewhere. All these forces led to an increase in rates and more frequent reliance on the spot market. (AT Kearney, 2018). In the second half of 2018, carrier's orders of increased capacity began to materialize; Industrial growth was slow; Colder weather caused decrease in shipment of produce and beverages; Anticipation of the trade tensions caused inventory build up which is still being worked through. All these forces led to the beginning of a softer market (Smith, 2019). While studying truckload spot rates one should keep in mind that such changes are recurrent, and that apart from predicting short term rates it is important to predict when the underlying nature of the market rate changes.

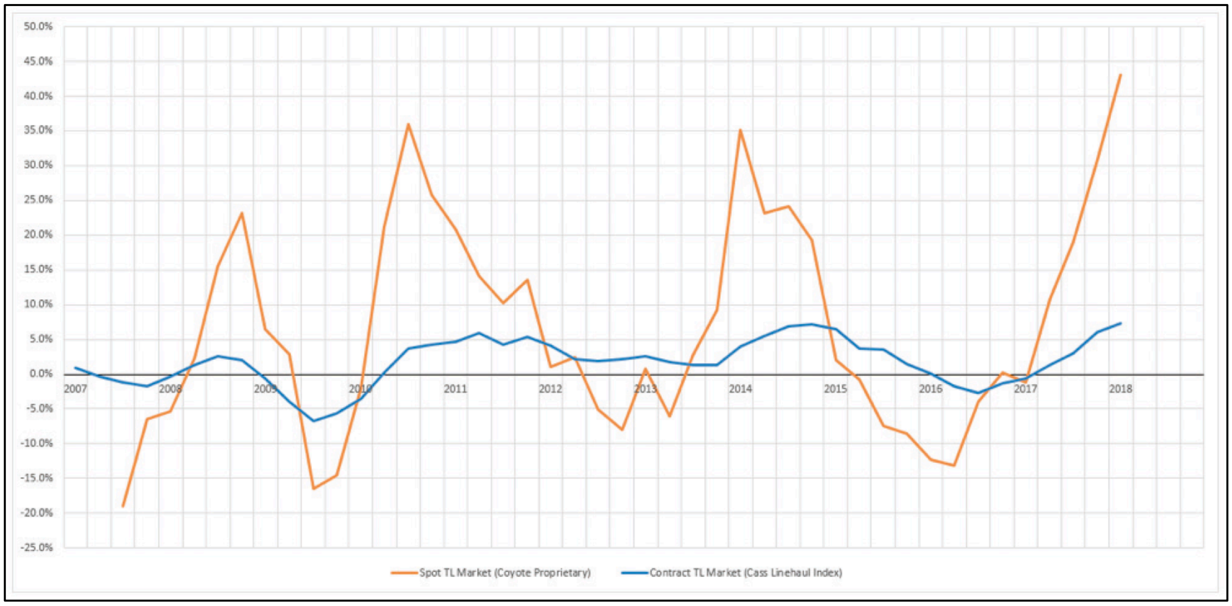


Figure 1. Truckload Market Cycles, Y/Y % change of quarters (Pickett, 2018)

2. MOTIVATION AND OBJECTIVES

Short term spot rate forecasts can help carriers estimate immediate cash flow. Shippers can use them to plan their operational budget and decide how far down the routing guide they need to look before opting for the spot market. Spot rates act as good leading indicators for contract rates, capacity, and other market trends in the future (Harding, 2017). Spot rates also lead futures markets (Tripathy, 2014). In March 2019 the industry witnessed the launch of Trucking Freight Futures Contract by Nodal Exchange, FreightWaves, and DAT (HDT Staff, 2019). Thus, spot rate forecasts can help participants in the futures market identify how much they should bid depending on which direction they want to hedge their risks. Additionally, spot rates are sometimes used to design index based flexible contracts in which the shipper pays a price relative to the market rate (Tsai, Saphores and Regan, 2011). In such cases too spot rate forecasts can be useful in estimating costs and negotiating prices. Moreover, transportation costs make up a significant portion of the total logistics costs for all companies and are used in decision models throughout the supply chain ranging from ordering decisions to facility location planning, transportation mode choice, vehicle routing, and inventory replenishment (Swenseth and Godfrey, 1996). We study short term forecasting of long haul truckload spot rates because it can help all players of the industry in numerous ways.

The objective of this paper is to understand how rates in the truckload spot market behave and to develop forecasting methodology to predict them for the near future (1-12 weeks ahead). Our aim is to answer the following 3 research questions. First, does the weekly spot rates time series exhibit detectable patterns or is it a Random Walk process? Secondly, are there lead economic indicators for forecasting short term spot rates? Finally, can we predict changes in the truckload spot market cycles?

3. LITERATURE REVIEW

3.1 Spot Rate Forecasting

The literature on forecasting freight rates is extensive but it is limited for truckload spot market in particular. Lindsey *et al.* (2013) used Linear Regression to model linehaul cost per mile for spot shipments of a US based 3rd Part Logistics (3PL) company. They used distance, volume-to-capacity ratio, origin and destination characteristics, type of equipment, market indices, and time of the year to determine prices at a lane level and individual shipment level. Scott (2015) modeled load-level estimates of spot premium for a large US based shipper. The regression model took lead time, lane, bid details, calendar week, and carrier into consideration. Their findings show that truckload prices of today influence the prices in the future. More recently Miller (2019) used ARIMA models to make monthly forecasts of Producer Price Index and average spot rates (in Dollars per mile) for full truckloads of dry van and reefers at a national level. Budak, Ustundag and Guloglu (2017) used a Feed-Forward Neural Network model and compared it to a Quantile Regression model to estimate truckload spot rates for a Turkish logistics company on a route level and at a national level. Input variables related to origin-destination characteristics, distance, load characteristics, vehicle type, prices, and month were used. These research help understand how different variables influence freight rates in various cases.

3.2 Concept Drift

Concept Drift is the phenomenon where the underlying structure and relationships of the dataset changes. In real life data this is a common occurrence. Models built on older datasets become obsolete and need to be updated in order to adapt to these changes (Žliobaitė, Pechenizkiy and Gama, 2016). Widmer and Kubat (1996), Tsymbal (2004), and Žliobaitė (2010) reviewed various methods of handling concept drift. These methods have been applied to numerous studies of classification tasks and some studies of time series analysis. One method that is discussed in these works that is of significance to us is incremental learning. Incremental learning is updating the model in an online manner i.e. when new data becomes available (Widmer and Kubat, 1996). They discussed different lengths of training windows, like including all of the available historical data in the training set or only considering the most recent instances. They also discussed how the forecasting model can either be updated implicitly, in a periodic fashion or explicitly, when a change signal is triggered.

Guajardo, Weber and Miranda (2010) implemented an implicit updating strategy for forecasting multiple time series with known seasonal patterns. At the end of every seasonal cycle they updated the model by including data from the most recent cycle into the training set. Their results showed that updating the model periodically produced better forecasts than the static model that is only trained in the first cycle of the data set.

Many researchers have studied explicit detection of concept drift in online datastreams, especially for classification tasks. However, very few use it for time series data. Cavalcante, Minku and Oliveira (2016) introduced Feature Extraction for Explicit Concept Drift Detection (FEDD) in time series. They claimed that concepts in a time series can be defined by certain features, and monitoring changes in those features help in detecting drift in the underlying concept. They identified gaps in previous work on drift detection: Patterns in the time series may not always be prior knowledge; Implicit detection i.e. updating the forecasting models in regular intervals can sometimes lead to overfitting; In case of methods using errors of prediction models as triggers for drift, the accuracy is conditional to the performance of the model; Finally, retrospective analysis is not useful in real time detection of drift. Their methodology was adjusted and adopted by Koesdwiady *et al.* (2018) to predict traffic flow.

3.3 Research Gaps

The aim of this paper is to contribute to truckload spot rates forecasting by filling several gaps in existing literature. Firstly, we want to make short term and more frequent forecasts for the truckload spot market. In current literature forecasts are made in monthly buckets for 1-6 months into the future. We forecast in weekly buckets for 1-12 weeks into the future as it is the preferred time frame for practitioners to act. Additionally, most of the existing work look into estimating the rates, given load and market characteristics in the same time period. We switch the focus to finding leading indicators for spot rates in order to predict the future. Finally, previous work do not address market cycles in the truckload spot market and how to detect and handle this drift while forecasting rates. We implement an explicit drift detection technique to predict when the market cycle changes, and update our forecasting models on detection of the drift; We also do periodic updates of the forecasting models. We thus introduce this methodology in the freight rate forecasting domain and contribute to the field of concept drift detection and handling by applying it to a real life dataset.

4. METHODOLOGY

4.1 Data Set

We use shipment transaction details from a leading US based supply chain consultancy company. As they cover a variety of large and small shipper and carrier companies, we consider it to be representative of the US truckload market. We look at over 4 million shipments of full truckloads of dry van totaling $4.9B in linehaul costs. All transactions are long haul (≥ 250 miles) shipments within the continental USA, tagged as 'Spot' shipment by the shipper. The time period is 6th April, 2015 – 26th May, 2019 (216 Monday-Sunday weeks). For this analysis we focus on average weekly spot rates at the national level i.e. Spot Cost Per Mile (S_CPM).

4.2 Checking for Random Walk

A time series can be characterized as a random walk if at every time period the value is a random step away from the value in the previous time period. This implies that the first order difference series is independent and identically distributed. Because the value at the next time period only depends on the value at the current time period, naïve forecasts serve as the best prediction for random walk processes. (Nau, 2014).

We check if the time series S_CPM is a random walk process in which case predicting it using autoregressive forecasting models will prove to be futile. We use the variance ratio (VR) test as described by Lo and MacKinlay (1989) to test the null hypothesis that the time series is a random walk process. We also use the augmented Dickey-Fuller (ADF) test as introduced by Dickey and Fuller (1981) to test the null hypothesis that the time series has a unit root. A time series with a unit root suggests non-stationarity and all random walk processes are non-stationary. We conduct the two tests on the whole time period and also on rolling windows of 13 (one quarter), 26 (half a year), and 52 weeks (one year).

4.3 Forecasting Using Multiple Linear Regression

If the tests indicate that the weekly spot rates indeed follow a random walk process, then a naïve forecast is more powerful than any other auto-regressive time series forecasting techniques. At each week w we want to forecast S_CPM for weeks $w+1$, $w+4$, $w+8$, and $w+12$. We create naïve forecasts as shown in equation 1.

$$S\_CPM_{w+1} = S\_CPM_{w+4} = S\_CPM_{w+8} = S\_CPM_{w+12} = S\_CPM_{w} \tag{1}$$

Next, we look at exogenous variables with lags of 1-52 weeks to check if there are lead indicators for spot market rates. We examine candidate economic indicators from Federal Reserve Economic Data (Federal Reserve Bank of St. Louis, 2019) as listed in Appendix A. We use predictor weeks in April, 2015 – March, 2016 (week 1-52) as the training set for the regression model. As we have a large number of candidate predictor variables (21 indicators x 52 lags = 1092), we need an efficient method of selecting the best group of predictor variables for the final model. We first shortlist indicators and their lags whose magnitude of correlation coefficient with S_CPM is higher than a threshold of 0.75 (selected experimentally). To fit the model, we use Elastic Net Regularization as described by Zou and Hastie (2005). This method is a combination of Lasso and Ridge regularization and minimizes ($SSR + \lambda_1 \times |slope| + \lambda_2 \times slope^2$) for a regression model. It is useful in cases when there are too many parameters to know which ones are relevant and which are not and when there is correlation between parameters (multiple lags of same indicator can be candidates). We implement this using 'lassoglm' function in MATLAB with $\lambda_1 = \lambda_2 = 0.5$ and a 10-fold cross-validation. We predict values for July, 2016 – May, 2019 (week 65-216) using this Static Model and compare the Mean Absolute Percentage Error (MAPE) to the Naïve forecast.

4.4 Handling Concept Drift

As discussed earlier, the truckload market goes through periodic cycles of tight and soft markets. A model trained on a soft market would be obsolete for forecasting rates in a tight market and vice-versa. To handle such concept drifts in the truckload market we adopt the following training methods:

1. <u>Implicit Update with Expanding Training Window</u> – We re-train the forecasting model every 13 weeks (one quarter), using all historical values, to adapt to the patterns in the new observations. In this case the full history of the time series is considered relevant in the model.

2. Implicit Update with Rolling Training Window – We re-train the forecasting model every 13 weeks, using data from only the previous 52 weeks. In this case older data is no longer considered relevant in predicting current values.

3. Update on Explicit Detection of Drift – We employ feature extraction for explicit drift detection as described by Cavalcante, Minku and Oliveira (2016). We claim that the following features of the difference series help define the underlying concept of the time series S_CPM:

(1) Mean

(2) Variance

(3) Skewness Coefficient

(4) Kurtosis Coefficient

(5) Autocorrelations of first 4 lags

(6) Bias – magnitude of the ratio of the average of positive values to the average of negative values, as shown in Equation 2.

$$Bias = \left|\frac{average(positive\ values)}{average(negative\ values)}\right| \tag{2}$$

We calculate the cosine distance between the base feature vector and the consequent feature vectors of window size $m = 13$ weeks, and monitor their exponentially weighted moving average (EWMA) with weighing factor $\alpha = 0.3$. We select thresholds for a warning signal ($W = 0.4$) and a concept drift signal ($C = 0.6$). Values of $m, \alpha, W,$ and C are chosen experimentally and by graphical inspection. When a warning signal is triggered, we train a new regression model using data from the last concept drift signal to the current warning signal. In case of a concept drift signal, we use the naïve forecast for the first 13 weeks after the signal and then use them to train a new regression model to predict the remaining weeks.

Explicit detection of concept drift also helps in anticipating when the market is going to change in the near future. This knowledge can be used by shippers and carriers to optimize their operations in ways discussed earlier.

5. RESULTS

First, we check if the time series S_CPM is a Random Walk process. We fail to reject the random walk null hypothesis ($H_{0,1}$) of the VR test with a p-value of 0.51. We also fail to reject the unit root null hypothesis ($H_{0,2}$) of ADF test with a p-value of 0.60. This indicates that for the whole time period of 4 years, the spot rates behave as a random walk process. For rolling windows of size 13 weeks we observe that $H_{0,1}$ is rejected in 21 instances and $H_{0,2}$ is rejected in 6 instances with one instance overlapping in both. Similarly, for rolling window size of 26 weeks $H_{0,1}$ is rejected for 8 instances and $H_{0,2}$ is rejected for 3 instances, with no overlap. Lastly, for rolling window size of 52 weeks only $H_{0,1}$ is rejected for 13 instances. These tests show us that largely the spot rates can be treated as a random walk process, with certain instances of break in structure. This gives us reason to believe that naïve forecasts are better than other auto-regressive time series forecasting techniques in predicting short term truckload spot rates. Morever, we should check for concept drifts in this time series.

We then predict the S_CPM values using the regression models and training methods discussed earlier. The MAPE results are given in Table 1 and the graphs comparing the predicted values to the actual values are shown in Figure 2.

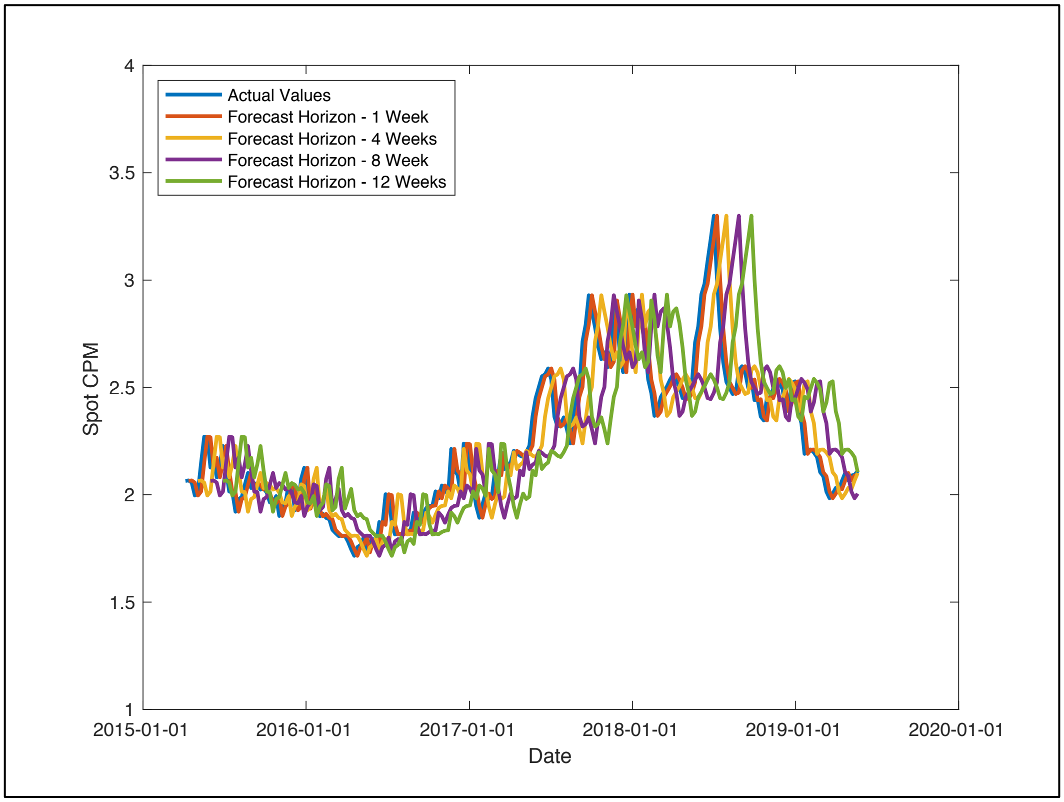
Table 1. MAPE Results of Forecasting Models

MAPE	**Forecasting Horizon**			
Model	**1 week**	**4 weeks**	**8 weeks**	**12 weeks**
Naïve Model	02.65%	06.04%	08.21%	09.20%
Static Model	19.44%	26.99%	26.15%	31.98%
Implicit Update with Expanding Training Window	14.18%	14.34%	12.38%	10.35%
Implicit Update with Rolling Training Window	9.69%	9.98%	11.88%	11.26%
Update on Explicit Detection of Drift	9.16%	11.91%	12.09%	12.44%

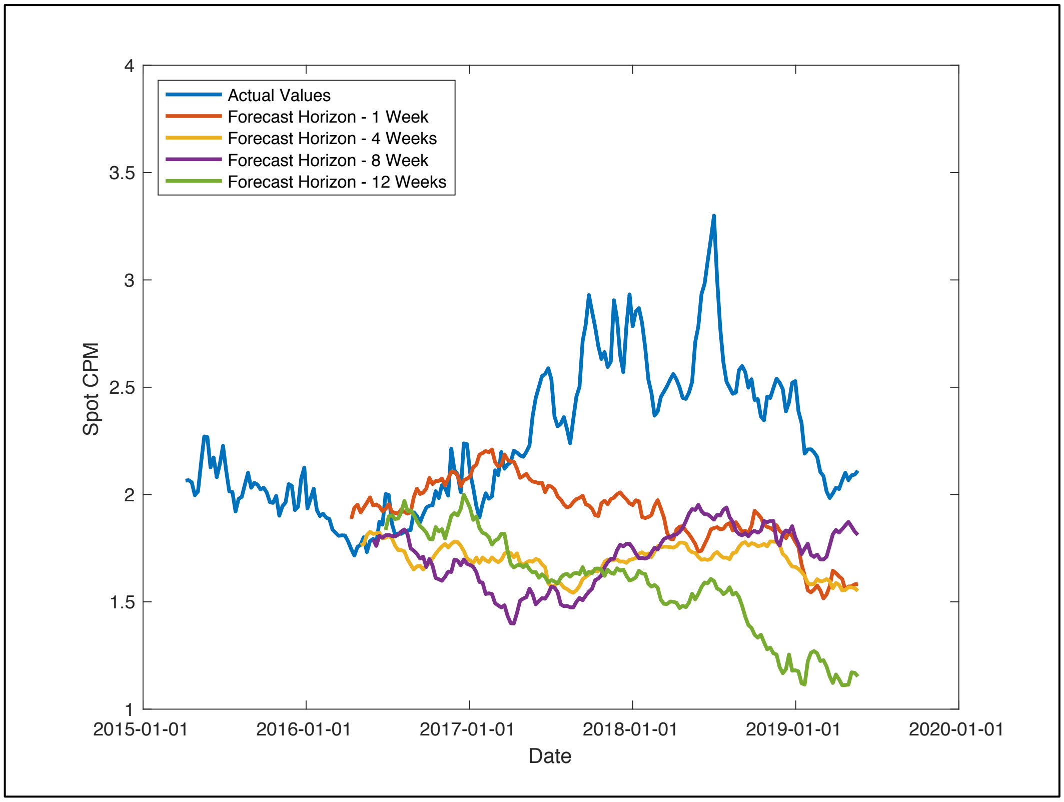
Naïve model has the lowest MAPE amongst all methods and all forecasting horizons. This provides further proof that weekly truckload spot rates are a Random Walk process. Some of the economic indices listed previously do act as lead indicators (Appendix B) for truckload spot rates, but the best option for prediction is still the most recent value of the spot rate itself. We note that as the forecasting horizon increased, the performances of the Implicit Update models became more comparable to the Naïve model. Thus, for forecasting horizons longer than the ones studied in this paper, more complex models, compared to a naïve model, may prove to be better at predicting spot rates.

The Static model has the worst performance as expected. The model was trained on a soft market period and thus underestimated the rates in the tight market period. Updating the models periodically decreased the forecasting errors. We observe that in most cases rolling window for training produced lower MAPE than an expanding window. This implies that only the most recent information is relevant while modelling short term spot rate volatility. Similarly, in most cases the Explicit Drift Detection method produced higher MAPE than the Rolling Training Window method as it used an expanding window for training when warning signals were triggered.

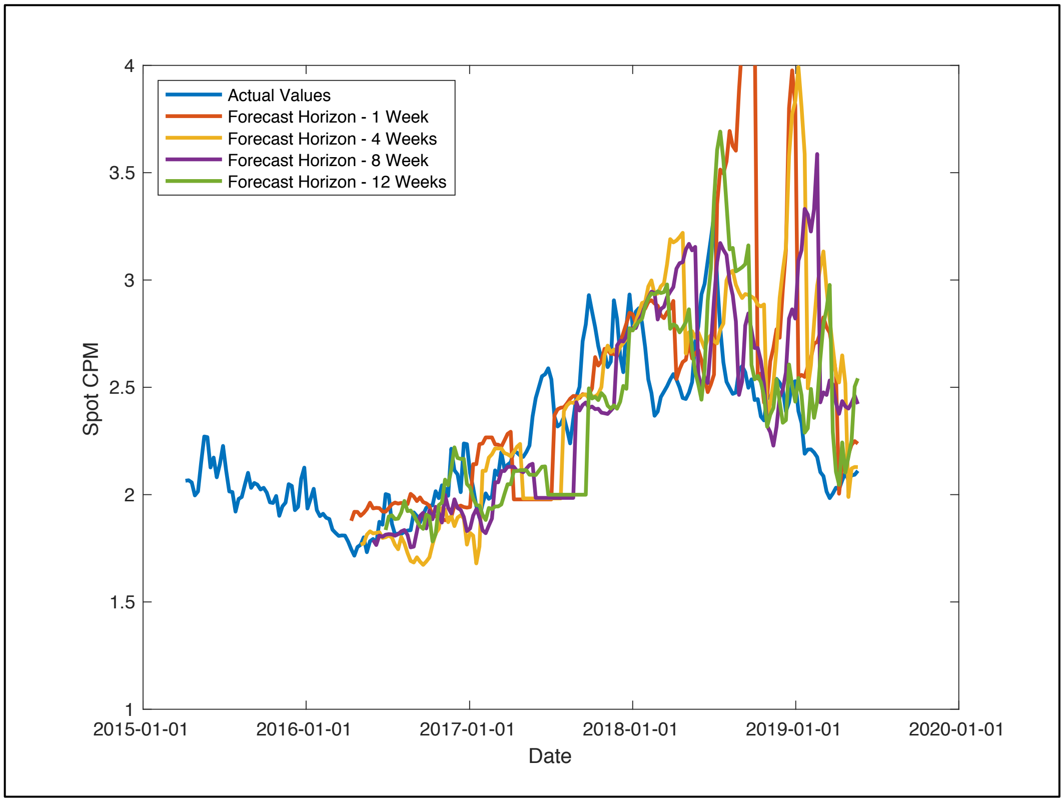
The dates of the signals triggered in the Explicit Drift Detection model are listed in Table 2. The concept drift signal is appropriately triggered in July, 2018 just before the market started shifting to a soft market period. As the method discarded the data before the drift signal and only used consequent data to train the new forecasting model, we observe that the predictions were closer to the actual values, as compared to the other methods (except Naïve), in this period. Additionally, the warning signals helped incorporate the larger crests and throughs of the time series in the training sets to produce forecast outputs in the appropriate range.



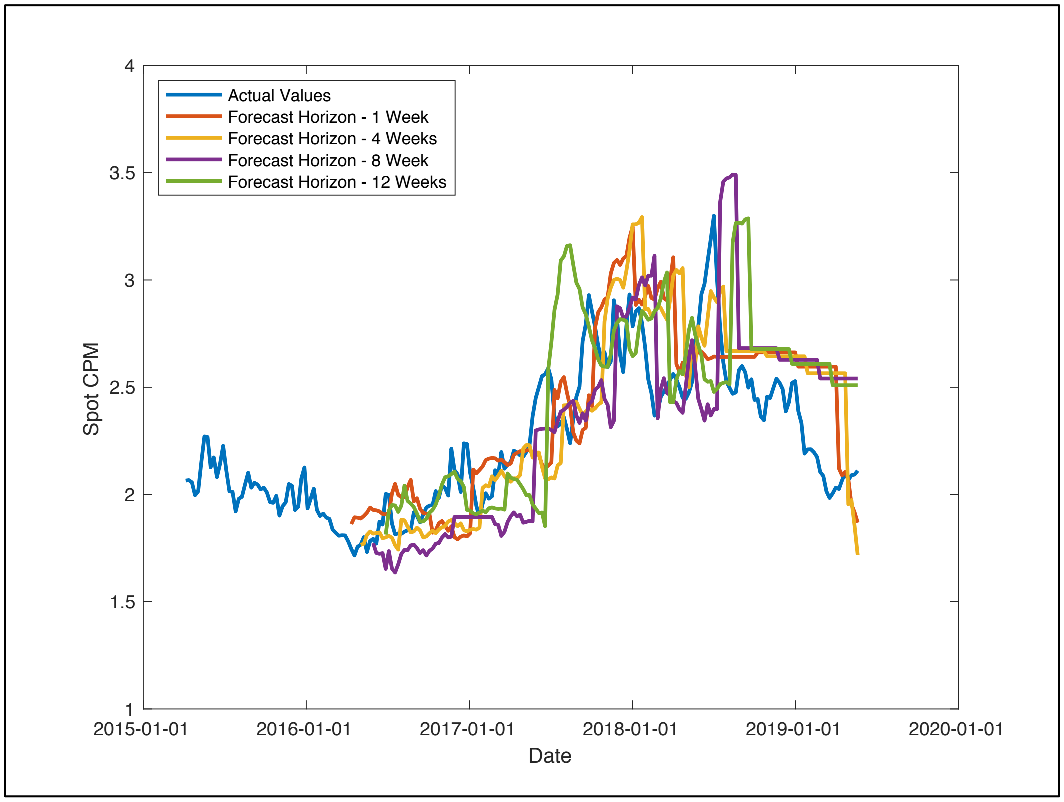
(a) Naïve



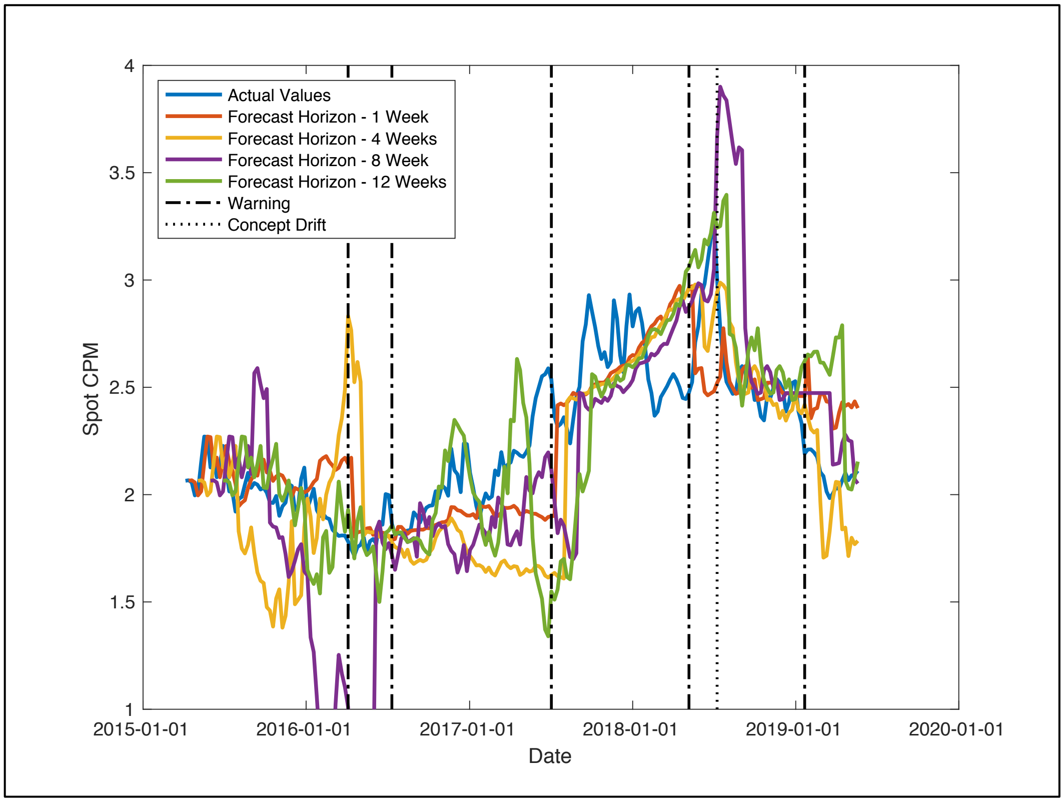
(b) Static Training



(c) Implicit Update with Expanding Training Window



(d) Implicit Update with Rolling Training Window



(e) Updating with Drift Signal

Figure 2. Predictions of Forecasting Models

Table 2. Signal Dates in Explicit Drift Detection Model

Week	Start Date of Week	Signal Type
53	4th April, 2016	Warning
67	11th July, 2016	Warning
118	3rd July, 2017	Warning
162	7th May, 2018	Warning
171	9th July, 2018	Concept Drift
199	21st January, 2019	Warning

6. DISCUSSION AND CONCLUSIONS

Forecasting short-term information for truckload spot market has numerous applications, but its volatile nature makes it difficult to predict. The time series of weekly Spot Cost Per Mile shows signs of being a Random Walk process, which is why we do not use auto-regressive forecasting models other than a Naïve model.

We list candidate market indices that can act as leading indicators for spot market rates and use their lags in a linear regression model using elastic net regularization. Morever, we handle concept drift by updating the model either periodically or based on a drift signal. The results indicate that updating the model improves the performance and that not all of the history is relevant in training. Even though some economic indicators display good predictive power for truckload spot rates, and updating the regression model lowers the MAPE, the Naïve model still outperforms for all forecasting horizons. Thus, we further affirm that the time series may indeed be a Random Walk and that the Naïve model is suitable for making frequent and short term forecasts of truckload spot rates.

Nonetheless, the information that the signals in the Explicit Drift Detection method indicate is still valuable in understanding where the market is heading in the near future. We are able to succesfully anticipate a shift from tight to soft market right before the Fall of 2018. Carriers can use such signals for resource planning such that appropriate capacity is available during the peaks and throughs of a tight and soft market, and lags are avoided. Shippers can revisit their contracts and accept higher rates in order to secure contract volume in a tight market and avoid larger spot premiums. Similarly, in anticipation of a soft market, shippers can re-negotiate lower contracts rates.

We contribute to the literature of truckload spot rate forecasting by creating short term and more frequent forecasts as compared to estimating current rates given market and load characteristics. We also contribute by introducing methodology for detecting onset of shift in truckload market cycles. Additionally, we extend the literature of online detection and handling of concept drift by applying it to a new real life case.

The values of various parameters in the models were chosen experimentally. They can be optimized, but in practice stakeholders do not look for exactly optimal solutions. Instead easy to implement solutions are more valuable, such as a naïve model that this research suggests. An extension to this research that the authors are working on is modeling how disruptions in truckload market, like natural disasters, affect prices.

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APPENDIX A

Federal Reserve Economic Data – Economic Indicators Definition

Variable	Definition
x_1	Trade Weighted U.S. Dollar Index: Broad, Goods, Index Jan 1997=100
x_2	Trade Weighted U.S. Dollar Index: Major Currencies, Goods, Index Mar 1973=100
x_3	Trade Weighted U.S. Dollar Index: Other Important Trading Partners, Goods, Index Jan 1997=100
x_4	Trade Weighted U.S. Dollar Index: Broad, Goods and Services, Index Jan 2, 2006=100
x_5	Trade Weighted U.S. Dollar Index: Emerging Markets Economies, Goods and Services, Index Jan 2, 2006=100
x_6	Trade Weighted U.S. Dollar Index: Advanced Foreign Economies, Goods and Services, Index Jan 2, 2006=100
x_7	S&P 500, Index
x_8	Dow Jones Industrial Average, Index
x_9	Wilshire 5000 Total Market Full Cap Index, Index
x_{10}	NASDAQ Composite Index, Index Feb 5, 1971=100
x_{11}	CBOE Volatility Index: VIX, Index
x_{12}	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma, Dollars per Barrel, Daily
x_{13}	Gold Fixing Price 10:30 A.M. (London time) in London Bullion Market, based in U.S. Dollars, U.S. Dollars per Troy Ounce
x_{14}	Leading Index for the United States, Percent
x_{15}	University of Michigan: Consumer Sentiment, Index 1966:Q1=100
x_{16}	Chicago Fed National Activity Index, Index
x_{17}	Kansas City Financial Stress Index, Index
x_{18}	KC Fed Labor Market Conditions Index, Momentum Indicator, Index
x_{19}	Personal consumption expenditures: Goods (chain-type price index), Index 2012=100
x_{20}	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma, Dollars per Barrel
x_{21}	Producer Price Index for All Commodities, Index 1982=100

APPENDIX B

All Input Variables Used in Final Regression Models

Variable	Lags	Variable	Lags
x_1	1	x_{12}	23, 24, 28
x_2	1-3	x_{13}	24, 25, 28, 29, 31
x_3	1-6	x_{14}	25, 26
x_4	2-8	x_{15}	26
x_5	3-10	x_{16}	29
x_6	3, 6, 7, 10, 11	x_{17}	26-33
x_7	3-9, 11-15	x_{18}	30-38
x_8	8-17	x_{19}	38-40
x_9	12-22	x_{20}	40-43
x_{10}	8, 16-31	x_{21}	39-50
x_{11}	23, 28, 31		