

Defining and Forecasting Truckload Market Cycles: A Deeper Dive

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ABSTRACT

The North American truckload (TL) market is characterized by inherent cyclicity, oscillating between periods of capacity surplus and shortage. This cyclicity creates significant uncertainty in capacity planning and pricing, making it difficult for market participants to anticipate shifts and respond effectively. This research develops a Logistic Regression-based early warning system to estimate the probability that the truckload market will shift into an expansionary or contractionary regime in a defined forecast horizon. Working in partnership with C.H. Robinson, we incorporate a diverse set of macroeconomic indicators and segment the analysis across Dry Van, Temperature Control, and Flatbed equipment types. Our methodology accounts for potential structural shifts in market behavior across pre-COVID, during-COVID, and post-COVID periods to evaluate whether traditional cycle dynamics remain valid in the current environment. Key findings indicate that specific leading indicators demonstrate predictive power for Dry Van and Temperature Control transitions, while Flatbed markets present unique challenges. The resulting probabilistic model provides a forward-looking tool for shippers, carriers, and brokers to shift from reactive market responses to proactive strategic planning, ultimately enhancing supply chain resilience and cost-effective freight procurement.

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Table of Contents

1. Introduction	3
1.1 Motivation	4
1.2 Problem Statement and Key Questions	4
1.3 Project Goals and Expected Outcomes	5
2. State of the Practice	5
3. Methodology	6
3.1 Methodology Selection	6
3.2 Data Collection and Preparation	7
3.3 Analytical Steps	9
4. Modeling	10
4.1 Model Selection	10
4.2 Model Architecture	10
5. Results and Discussion	12
5.1 Expansion Model Results	13
5.1.1 Dry Van Expansion Model Results	13
5.1.2 Temperature Control Expansion Model Results	14
5.1.3 Flatbed Expansion Model Results	15
5.2 Contraction Model Results	15
5.2.1 Dry Van Contraction Results	15
5.2.2 Temperature Control Contraction Results	15
5.2.3 Flatbed Contraction Results	16
5.3 Model Prediction Results	16
5.4 Multi-Horizon Forecast	17
5.5 Limitations	18
6. Recommendations	18
6.1 Management Recommendations	18
6.2 Future Work	19
Appendix: Additional Model Figures	19
References	20

1. Introduction

Characterized by constant rebalancing between supply and demand, the truckload (TL) market functions in a highly cyclical manner, oscillating between periods of capacity surplus and shortage (Pickett, 2025). To further define the cyclicity, Kirirak and Roman (2025) identified four distinct, recurring phases within these market swings: Expansion, Peak Transition, Contraction, and Trough Recovery. These phases are defined by the relationship between contract rates, spot rates, and the Spot Premium Ratio. While contract rates represent fixed, pre-negotiated prices for specific lanes—typically established for six to 12 months within a shipper/carrier partnership—spot rates are market-driven prices negotiated for individual, immediate shipments. The interaction between these two pricing models is captured by the Spot Premium Ratio, which measures the percentage difference between average spot and contract rates.

The truckload cycle phases are determined by the behavior of key pricing indicators, such as year-over-year (YoY) spot and contract rates and the Spot Premium Ratio. These indicators reflect shifts in supply and demand and form the basis for identifying when the market moves into each phase of the TL cycle.

Kirirak and Roman (2025) defined the market cycle phases as follows:

- **Expansion:** This phase starts when both the YoY spot rate and the Spot Premium Ratio shift from negative to positive over time.
- **Peak Transition:** This phase begins when both the YoY spot and contract rates, which are both positive, intersect.
- **Contraction:** This phase starts when both the YoY spot rate and the Spot Premium Ratio cross below zero over time.
- **Trough Recovery:** This phase occurs when both the YoY spot and contract rates, which are both negative, intersect.

Figure 1 illustrates how the four TL market phases are defined based on the YoY behavior of spot rates, contract rates, and the Spot Premium Ratio.

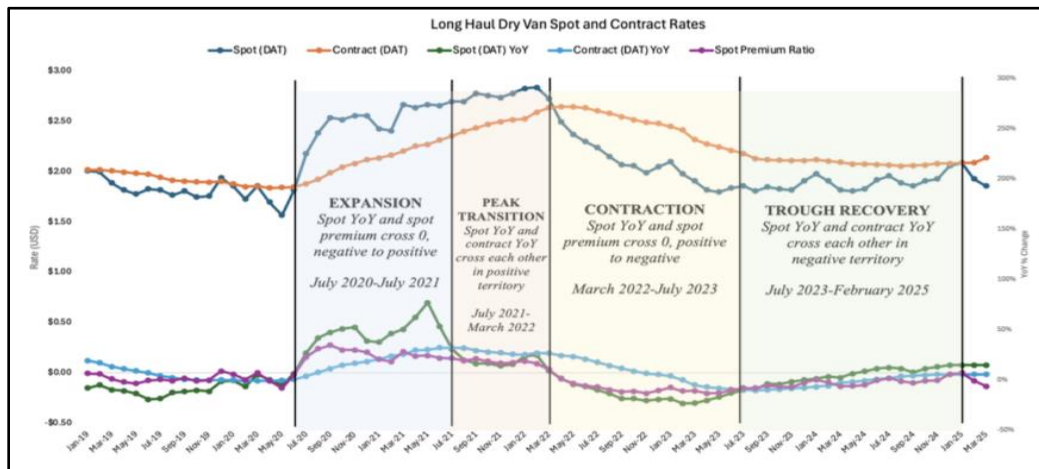


Figure 1. Cycle Definition During the COVID-19 Pandemic Period (Kirirak and Roman, 2025)

These four shifts shown in Figure 1 are influenced by changes in demand, supply, and broader macroeconomic factors such as Imports, Housing Starts, and Residential Construction. Because it is unclear how and which of these factors contribute to spot and contract prices and resulting freight

market dynamics, the truckload industry struggles to forecast cycle transitions reliably. Lacking a method to anticipate cycle shifts, shippers, carriers, and brokers must respond reactively to evolving market conditions, rather than anticipating those shifts. Anticipating shifts rather than reacting to them allows all three parties to level-set their rates and better plan capacity as needed. Shippers can protect the bottom line by understanding when to lock in long-term contracts rather than playing in the spot market, carriers can decide whether they want to be aggressive or defensive in their pricing, and brokers can manage the gap between what the shipper pays and what the carrier charges.

1.1 Motivation

Our partner company, C.H. Robinson, is headquartered in Eden Prairie, Minnesota. With more than 83,000 shipper customers and 450,000 contract carriers, the company manages 37 million shipments and \$23 billion in freight annually (C.H. Robinson, 2025).

As one of the largest Third-Party Logistics (3PL) companies in the North American market, the company's key focus is leveraging its scale and tailored solutions to provide sustainable and cost-effective freight transportation (Schlecht, 2025). A current initiative focuses on advancing truckload forecasting and market segmentation by equipment type and region to better manage market cycles, optimize routing, and support a more resilient supply chain.

To address this uncertainty, C.H. Robinson is motivated to develop more accurate and granular forecasting tools that can anticipate cycle transitions and provide early signals to stakeholders. For example, in 2024 and 2025 they and their customers were looking to understand when the ongoing Trough Recovery period would end, as it has lasted longer than typical Trough Recovery periods. Kirirak and Roman (2025) identified the two dependent variables, spot and contract rates, that indicate a shift in the truckload industry's business cycles and the independent variables that have historically influenced the dependent variables. They used a Vector Autoregression (VAR) approach to model Dry Van Truckload cycles through spot and contract forecasts. This work takes a different approach by developing predictive models of the timing of market expansions and contractions.

Through this project, C.H. Robinson has a more reliable, data-driven approach for managing truckload cycles, offering customers more precise insights into the timing of the different phases of these cycles.

1.2 Problem Statement and Key Questions

Our key objective is to more accurately forecast the timing of the truckload market cycle shifts. Rather than predicting the exact level of spot or contract rates, this research focuses on estimating the probability that the truckload market will shift into an expansionary or contractionary regime in a defined forecast horizon. We expand on the existing VAR model from Kirirak and Roman's 2025 capstone project with C.H. Robinson. Specifically, we introduce new data from the past year, including leading macroeconomic indicators, and segment the model into subgroups. Segmentation is important because different freight types often respond differently to changes in market conditions and may provide earlier or more distinct signals of upcoming cycle shifts.

In that context, we aim to answer the following questions:

1. What additional variables, beyond those examined in prior research, may improve the ability to predict when truckload market cycle transitions will occur?
2. What variables and models can be used to predict the timing of market cycle phases for other equipment types (i.e., Flatbed and Temperature Control)?

1.3 Project Goals and Expected Outcomes

The goal of this project is to provide C.H. Robinson with a more accurate forecasting model for the timing of truckload market cycles. By researching alternative forecasting methods and testing new variables, the project aims to improve the company's ability to predict cycle transitions and identify leading indicators. This enhanced forecasting capability will allow C.H. Robinson to support its customers with more accurate pricing, capacity planning, and procurement strategies, strengthen carrier relationships, and improve internal planning during periods of market uncertainty.

The deliverables to the company will include:

1. A refined forecasting model of the probability of a cycle shift that incorporates segmentation and integrates new explanatory variables,
2. Expansion of this model to Temperature Control and Flatbed, and
3. Visualizations to illustrate cycle behavior and provide stakeholders with clearer insights into the probability of timing of market transitions.

C.H. Robinson will be able to use and regularly update the forecasting model, ensuring it remains adaptable to evolving market conditions and incorporates new data sources.

2. State of the Practice

We reviewed academic research and recent industry analyses addressing the dynamics of the TL market, macroeconomic factors that affect the market, and existing predictions for the next cycle shift.

Caplice (2021) provides clarity on the size and behavior of the spot and contract markets, the significance of TL transportation, and the competitive nature of the industry. Contract shipments represented 84% of transaction volume in DAT's Freight Market Intelligence Consortium (FMIC) in 2021, highlighting the dominance of contracted shipments in the TL market. DAT is a freight marketplace and data analytics platform that aggregates pricing and load board data across the North American trucking industry. Because the TL transportation market accounts for roughly 2% of U.S. GDP and over \$400 billion in annual revenue, improving our ability to understand and forecast its cycles has significant implications for carriers, shippers, and brokers nationwide.

The competitive landscape of the truckload market is characterized by a significant power imbalance between thousands of independent carriers and shippers with divergent economic objectives. Acocella (2020) observes these opposing goals frequently result in "power flips" dictated by available capacity. In a "soft" market, an oversupply of freight services relative to demand grants shippers the leverage to negotiate lower pricing. Conversely, a "tight" market occurs when demand exceeds supply, shifting the advantage to carriers who can then be more selective and command higher rates. Understanding these structural shifts is essential for identifying the underlying factors that influence the broader truckload market cycle.

Pickett (2018) was among the first to put the TL market cycle into context, identifying the recurring patterns of capacity and rate fluctuations that drive the broader truckload market. Building on this foundation, Kirirak and Roman (2025) conducted industry research to understand the four phases within a full TL market cycle: Expansion, Peak Transition, Contraction, and Trough Recovery. Additionally, they investigate the factors contributing to these phase shifts. Their work provided three key contributions relevant to our research:

1. A summary of current industry practices and challenges
2. The structured cycle phase framework provided above

3. A forecasting approach predicting the next phase shift

Trucking industry analysts and freight market researchers generally consider spot and contract rates to be key indicators of current market conditions. When spot and contract rates go up, the market is considered “tight.” When these rates decrease, the market is considered “loose.” When it comes to market predictions, the biggest challenge that the truckload industry faces is the absence of industry-accepted forecasting approaches and benchmarking methods. For example, some industry experts believe using a year-over-year comparison of certain metrics is best, while others use indexing approaches that measure the change of variables relative to a fixed baseline. While both ways can generate similar findings, it has proven difficult to build a standardized forecasting method that is capable of being used across the entire industry (Kirirak and Roman, 2025).

At the time of this writing, the market has been in a Trough Recovery phase for three years—an unprecedented amount of time, as this phase typically lasts eight months.

The VAR model developed by Kirirak and Roman (2025) initially predicted an Expansion phase in February 2025. However, the market remained in Trough Recovery and did not meet the model’s criteria for expansion. This divergence suggests that pre-COVID patterns may not fully capture post-COVID dynamics, indicating a potential structural break. Several factors may explain this shift, including a rapid post-COVID capacity surge followed by slower-than-expected capacity exit, elevated interest rates dampening demand, softer consumer goods demand, and ongoing trade and supply chain uncertainty. Together, these dynamics suggest that post-COVID market behavior differs from historical cycles, highlighting the need for models trained on more recent data.

We reviewed multiple publicly available industry reports and market commentaries discussing current truckload market conditions and the potential impact of post-COVID structural changes on freight cycles. One such example was RXO’s “*Q4 2025 Truckload Market Forecast: Spot & Contract Rate Trends*” (RXO, 2025), which highlighted trends such as regulatory pressures on carrier capacity, carrier exits, and ongoing market imbalance. These reports reflect broader industry perspectives and help frame the broader market discussion surrounding whether traditional truckload cycles continue to behave similarly in the post-COVID environment.

From analyzing each of these pieces of research, we are able to better understand the problem at hand, its significance, and how to potentially approach solving it. We build our methodology first by analyzing other macroeconomic factors that were not tested by Kirirak and Roman (2025). Next, we examine market behavior during pre-COVID, during COVID, and post-COVID periods to test the claim that the cycle may be broken. Finally, using insights from C.H. Robinson as well as our advisors, we develop a different forecasting model to identify a more accurate approach to predicting the timing of the next phase in the TL market cycle.

3. Methodology

This section outlines our methodological approach to evaluate the drivers of TL market cycles and identify forecasting strategies to anticipate cycle transitions.

3.1 Methodology Selection

Drawing on industry research, prior academic work, and guidance from the C.H. Robinson team and our academic advisors, we structured our methodology around two major components.

First, we expand the set of macroeconomic variables and segmentation techniques beyond those included in the prior capstone. This allowed us to test how additional economic indicators (Residential and Nonresidential Construction, U.S. Imports, Diesel Prices, etc.) interact with truckload spot and

contract rates across three equipment types (Dry Van, Temperature Control, and Flatbed) and eight regions. These exploratory analyses help determine which variables meaningfully influence TL pricing behavior and whether certain equipment types or regions act as early-cycle predictors.

Second, we examine how the TL market behaves across distinct structural periods—pre-COVID, during the height of COVID, and post-COVID—to assess whether the underlying market cycle has fundamentally changed. Industry research suggests that the TL cycle may have been behaving differently since 2020, and our segmented analysis helps evaluate whether structural breaks or shifts in variable relationships must be accounted for when designing the new forecasting model.

After identifying critical variables and market behaviors across structural periods, we evaluate various forecasting approaches. Our strategy involved comparing time-series and econometric techniques to determine which model best predicts TL market cycle shifts. This evidence-based selection ensures the final method is chosen for its analytical performance rather than based on assumptions.

3.2 Data Collection and Preparation

C.H. Robinson supplied a dataset encompassing all three equipment types, including operational and pricing data such as spot and contract rates, routing guide metrics, load-to-truck ratios, and tender acceptance rates, to facilitate our exploratory research. Beyond this primary operational and pricing data, we identified several macroeconomic indicators from the U.S. Energy Information Administration (EIA) and Federal Reserve Economic Data (FRED). These variables include factors previously identified as highly significant by Kirirak and Roman (2025), as well as novel indicators they did not investigate. Serving as essential proxies for international trade flows, manufacturing output, and construction activity, these macroeconomic markers act as critical drivers of demand within the truckload freight industry. Table 1 summarizes the variables, definitions, and data sources used in the model. For variables disaggregated by equipment type, Dry Van values are used to calculate the reported minimum, maximum, and average.

Variable	Definition	Source	Min	Max	Average
Spot Line-haul CPM by Equipment Type, Nationally and Outbound Region (DV)	The average cost per mile (CPM) for spot by equipment type and outbound region	C.H. Robinson	1.14	2.72	1.65
Contract Line-haul CPM by Equipment Type, Nationally and Outbound Region (DV)	The average cost per mile (CPM) for contract by equipment type outbound region	C.H. Robinson	1.27	2.65	1.75
National Average Miles Traveled for Contract by Equipment Type, Nationally and Outbound Region (DV)	The mean distance of all recorded hauls for contract loads across the country outbound region	C.H. Robinson	930	1071	988.77
National Average Miles Traveled for Spot by Equipment Type, Nationally and Outbound Region (DV)	The mean distance of all recorded hauls for spot loads across the country outbound region	C.H. Robinson	787	953	891.77

Total Routing Guide Depth (RGD)	The average number of carriers a shipper contacts in their prioritized list before accepting the load	C.H. Robinson	1.14	2.74	1.63
RGD by Equipment Type (DV)	The average number of carriers a shipper contacts in their prioritized list before accepting the load by equipment type	C.H. Robinson	1.12	2.96	1.62
Load-to-Truck Ratio (LTR) by Equipment Type (DV)	The number of available loads relative to the number of available trucks by equipment type	C.H. Robinson	0.92	9.68	4
Total First Tender Acceptance (FTA)	The percentage of time the primary carrier in a routing guide accepts a load tender	C.H. Robinson	0.68	0.92	0.82
FTA by Equipment Type (DV)	The percentage of time the primary carrier in a routing guide accepts a load tender by equipment type	C.H. Robinson	0.66	0.93	0.82
Class 8 Total Backlog	The total number of heavy-duty trucks that have been ordered from manufacturers but are not yet built	ACT Research	53473	264317	129905.73
Class 8 Total Cancel	The total number of previously placed orders for heavy-duty trucks that were terminated before production	ACT Research	4	3666	541.63
Class 8 Sleeper Backlog	The total number of heavy-duty trucks equipped with sleeping compartments that have been ordered from manufacturers but are not yet built	ACT Research	81	2874	988.23
Class 8 Sleeper Cancel	The total number of previously placed orders for heavy-duty trucks equipped with sleeping compartments that were terminated before production	ACT Research	0	415	12.21
Total Construction Spending: Nonresidential in the United States	Total monthly value of work performed on new structures, in millions of dollars	Federal Reserve Economic Data	545802	1272216	862740.96
Total Construction Spending: Residential in the United States	Total monthly dollar value of all work performed on housing units, in millions of dollars	Federal Reserve Economic Data	265032	988269	634415.04
Industrial Production: Manufacturing: Nondurable Goods: Paperboard Container (SA)	Total monthly output of all U.S. facilities manufacturing corrugated and solid fiber boxes and other paperboard packaging	Federal Reserve Economic Data	88.91	105	96.90
Imports of Goods for United States	Total monthly value of physical goods entering the U.S., excluding import duties, freight, and insurance costs, in millions of dollars	Federal Reserve Economic Data	162949.75	342602.92	220692.11
Imports of Goods for California	Monthly total value of foreign-manufactured and non-manufactured commodities whose final designated destination for consumption or further processing is California, in millions of dollars	Federal Reserve Economic Data	26512.66	47247.46	36273.10

Industrial Production: Manufacturing: Nondurable Goods: Chemical	Monthly inflation-adjusted output of all U.S. establishments engaged in transforming organic and inorganic raw materials by a chemical process	Federal Reserve Economic Data	90.96	108.4	100.17
New Privately-Owned Housing Units Started: Total Units	Monthly number of new privately owned housing units on which construction has begun	Federal Reserve Economic Data	708	1820	1259.38
Industrial Production: Manufacturing	Monthly index measuring the real output of U.S. manufacturing industries	Federal Reserve Economic Data	79.86	102.04	96.9
Industrial Production: Manufacturing: Durable Goods: Motor Vehicles and Parts	Monthly index measuring the real output of U.S. manufacturing industries producing durable goods in the motor vehicles and parts sector	Federal Reserve Economic Data	20.58	111.38	99.41
US On-Highway Diesel Fuel Prices	Monthly average retail price per gallon paid by consumers for ultra-low sulfur diesel at self-service filling stations	Energy Information Administration	2	5.75	3.44

Table 1. Model Input Variables and Data Sources

3.3 Analytical Steps

To understand the behavior of the truckload market, we conducted several analyses across macroeconomic indicators, TL pricing, equipment types, time periods, and regions. We start by mapping correlations among all key variables, including spot and contract CPM, average miles, RGD, FTA, and macroeconomic indicators. This analysis allowed us to identify initial patterns in how changes in economic activity relate to changes in TL pricing. By segmenting these correlations by mode and region, we observe where relationships are strongest, weakest, or potentially indicative of early-cycle movement. Our analysis revealed that Housing Starts exhibited some of the strongest correlations with contract rates across all three equipment types, a pattern not observed within the spot market.

Structural shifts in the TL cycle following the COVID-19 pandemic were assessed by comparing the Trough Recovery phase from January 2019 to July 2020 with the post-COVID phase beginning in July 2023. The analysis focused on the evolving relationship between spot rates and macroeconomic indicators across these two periods. The absolute average correlation for key metrics, including Residential and Nonresidential Construction, Class 8 Sleeper Backlog, and Class 8 Total Backlog, dropped from 0.529 in the pre-pandemic phase to 0.141 in the current environment. This significant decline in correlation strength indicates that the truckload market has undergone fundamental changes since the onset of COVID.

Next, we conduct lead/lag analyses to quantify timing relationships between variables. Using cross-correlation functions, we measure by how many months certain macroeconomic indicators lead or lag changes in TL spot and contract pricing. We also test timing differences across equipment types (e.g., whether Flatbed leads Dry Van or Temperature Control) and across regions to identify early moving markets. Housing Starts led contract rates across all equipment types, but the timing differs by mode. Flatbed responds earliest, with a four month lead, followed by Dry Van at one month, while Temperature Control reacts approximately three months later. RGD tends to lead spot rates by roughly one to three months, particularly for Temperature Control. Conversely, U.S. Imports consistently lag TL pricing by four to six months across all equipment types. These results show that timing relationships vary across segments and indicators, so it's important not to assume one consistent pattern.

The insights from the correlation, structural, and segmentation analyses inform the forecasting approach by identifying relevant predictors and their lead-lag relationships. These findings guide model selection by ensuring that only variables with demonstrated predictive value and appropriate timing are included. We model each direction separately. The Expansion model estimates the probability that the market will be in an expansionary regime in three months from now, and the Contraction model estimates the probability that the market will be in a contractionary regime three months from now.

4. Modeling

This section outlines the modeling framework developed to estimate the probability of a transition in the truckload market cycle over a defined forecast horizon. We implement a Logistic Regression model that incorporates lagged pricing indicators and macroeconomic variables identified through correlation and lead-lag analysis. This probabilistic approach enables a forward-looking early warning system, aligning with shippers’, carriers’, and brokers’ needs to anticipate structural changes in the TL market rather than react to them.

4.1 Model Selection

The objective of our modeling approach is not to predict the exact value of spot or contract rates, but rather to estimate the probability that the truckload market will be in an expansionary or contractionary regime in a defined forecast horizon (X months). Because our outcome of interest is binary, we selected a Logistic Regression model as the primary forecasting method.

Unlike traditional time-series models such as VAR and AutoRegressive Integrated Moving Average (ARIMA), which forecast continuous values, Logistic Regression directly models the likelihood of an event occurring. In our context, the event is the market being in an expansionary or contractionary regime in the selected forecast horizon.

Another key reason for selecting Logistic Regression is interpretability. Because our audience includes business stakeholders, the model must provide transparent insights into which macroeconomic indicators meaningfully influence the probability of a cycle change. Logistic Regression produces standardized beta coefficients and statistically interpretable p-values, allowing us to identify which indicators serve as early warning signals. This interpretability makes it easier for C.H. Robinson to operationalize model results in decision-making processes. For example, the transparency of Logistic Regression allows the C.H. Robinson team to tie model outputs directly to observable market signals, enabling proactive adjustments regarding upcoming pricing trends rather than a reactive approach.

4.2 Model Architecture

Traditional time-series models focus on predicting the current state of the market. To address the need for forward-looking insights, our model uses a temporal offset, shifting the target variable (the market phase) forward by X number of months. We train the model to recognize the “incubation period” of a market shift—defined as the time between early changes in market indicators and the observable transition in the truckload market phase. This transforms the analysis from reactive management to employing a system of early warning signals. A Logistic Regression Equation is given as:

$$P(Y = 1 | X) = \frac{1}{1 + e^{-(B_0 + B_1 X_1 + B_2 X_2 + \dots + B_n X_n)}}$$

where:

Y is a binary outcome variable equal to 1 if a market phase shift occurs and 0 otherwise

$P(Y=1|X)$ is the predicted probability that a market phase shift will occur given the input features

X_1, \dots, X_n are the lagged macroeconomic and pricing indicators

β_0 is the intercept, representing the baseline log-odds of the market

β_1, \dots, β_n are the coefficients corresponding to each lagged indicator

e is Euler's number, a mathematical constant essential for describing continuous growth (approx. 2.718)

In the model, we use macroeconomic indicators and pricing variables, including Spot Premium Ratio and YoY spot rate, to estimate the likelihood of a phase shift within the forecast horizon. We start by cleaning the data, dropping any empty values, and ensuring all columns are treated as numbers.

Because C.H. Robinson's rate data does not extend as far back as several macroeconomic indicators, we extend the C.H. Robinson series back to 2012 using historical relationships with data from DAT data. We first confirm strong correlations between DAT's and C.H. Robinson's spot and contract rates over their overlapping period, then estimate linear relationships and apply them to earlier DAT observations to backcast C.H. Robinson values. This allows the model to operate on a consistent dataset from April 2012 to December 2025.

We then implement lead-lag analysis to determine the timing relationship between indicators and truckload pricing. Rather than assuming variables impact the market immediately, we test how many months each indicator leads or lags changes in rates. This informs how variables are shifted in the model to align current signals with future outcomes.

We implement the lead-lag analysis because in business cycles, causes and effects rarely occur simultaneously. For example, an increase in Housing Starts does not immediately impact the truckload spot market; the effect occurs several months later when construction activity begins and material demand increases. We therefore shift the data so the model can evaluate the "state of the world three months ago." We then shift the target variable backward to align today's indicators with the future outcome. As a result, the model is trained to answer: "Given the specific signals today, what is the statistical likelihood that the market will be in an expansionary or contractionary regime in three months?"

Next, we normalize the variance in each of our columns. Because the input variables are measured on different scales, with Housing Starts measured in the millions versus spot rates measured in dollars, we scale the data to be similar in magnitude. This scaling prevents the model from assigning disproportionate importance to variables simply because they have larger numerical values. Accordingly, we apply Z-Score Standardization, centering every variable around a mean of zero and a standard deviation of one. Now, the model compares a move in housing to a move in rates on equal ground using coefficients.

Once standardized, we fit a Logistic Regression model to estimate the probability of a market shift. Model significance is evaluated using p-values, with values below 0.05 indicating statistically meaningful predictors.

To translate these results, the coefficients are subsequently restored to their original units to ensure interpretability. This rescaling facilitates a more intuitive analysis of the model's outputs, bridging the gap between standardized statistical results and real-world applications. Rescaling better explains what happens to spot rates if, for example, Housing Starts increase by 500,000. To do this, we divided the results by the original standard deviations, rescaling them back to their real-world units (dollars, units, etc.).

To communicate results, we develop two visualizations. First, an importance chart ranks lagged predictors based on their contribution to transition probability as shown in Figure 3, highlighting the most influential indicators. Second, a probability timeline tracks the model’s predicted likelihood of a shift over time, serving as a forward-looking indicator of changing market conditions as visualized in Figure 4.

The initial model is refined through several iterations to improve performance and ensure stability. These refinements include aligning variables with the forecast horizon, addressing multicollinearity, and extending the framework across freight modes and contractionary periods.

To better align with the forecasting objective, the correlation analysis is restructured to focus on the relationship between predictors and the phase shift target variable, rather than spot CPM. This allows for more accurate identification of lead-lag relationships that are relevant to predicting market transitions.

One challenge during this development phase is addressing possible multicollinearity. Multicollinearity occurs when independent variables are intercorrelated with each other, causing high standard errors and unstable coefficients. First, we employed Variance Inflation Factor (VIF) testing to identify any redundant variables. VIF measures how much the variance of an estimated regression coefficient increases due to collinearity between predictors. We initially use a VIF threshold of 5, a commonly used benchmark for identifying multicollinearity in regression models. However, applying this threshold proved too restrictive, as it led to the removal of several variables that were economically meaningful and statistically significant.

We therefore transition to a correlation-based filtering approach, which allows for more targeted identification of highly correlated variable pairs while retaining the most informative predictors. This approach provides greater control over variable selection and ensures that key market indicators are not excluded solely due to statistical thresholds. Based on this refinement, we also incorporate additional variables—Load-to-Truck Ratio (LTR) and Diesel Fuel Prices—due to their known relevance to supply-demand balance and carrier cost structures. These additions improve the model’s ability to capture underlying market conditions.

The modeling framework is then extended to contractionary periods. While the overall structure remains consistent, there are three distinct characteristic changes:

1. The definition of the target variable is reversed. The binary classifier initially coded as 1 for expansionary periods and 0 for contractionary periods is changed to represent contractionary periods with 1 and expansionary periods with 0.
2. The regime definition is reconfigured. In the contractionary models, a contraction period is now described as the Spot Premium Ratio and YoY spot rate being negative.
3. The dataset is confined to only the 2012–2022 period. This captures the full cycle leading into the most recent contraction and provides a benchmark for validating the model’s directional accuracy.

5. Results and Discussion

This section presents the findings from the Logistic Regression models and interprets their economic significance within the broader truckload market context. For modeling purposes, the four-phase truckload cycle is grouped into two regimes: expansionary (Expansion and Peak Transition) and contractionary (Contraction and Trough Recovery). We evaluate model performance in predicting transitions into these regimes. We begin with the Expansion model results, followed by the Contraction model results with the short-term forecast, and conclude with a multi-horizon forecast.

5.1 Expansion Model Results

The purpose of developing the Expansion models is to evaluate the predictive accuracy of the model by identifying indicators that precede transitions into expansionary phases, allowing C.H. Robinson to anticipate when the next Expansion phase will occur.

5.1.1 Dry Van Expansion Model Results

To identify the drivers of Expansion in the Dry Van market, we use lagged variables and a correlation matrix to evaluate relationships among the candidate predictors and identify potential multicollinearity. Figure 2 displays the pairwise Pearson correlations between the lagged predictors considered for the model. Several variables exhibit strong correlations, indicating potential multicollinearity between predictors. To address this issue, a correlation filtering threshold of 0.8 is applied. We also evaluate stricter thresholds of 0.6 and 0.3; however, these thresholds remove a large number of predictors, resulting in models where most variables are no longer statistically significant. As a result, the 0.8 threshold provides the best balance between reducing multicollinearity and retaining meaningful predictors. Variables exceeding this threshold are removed to prevent redundant information from destabilizing the regression coefficients. As shown in Figure 2, 13 key predictors were kept for analysis after multicollinearity testing.

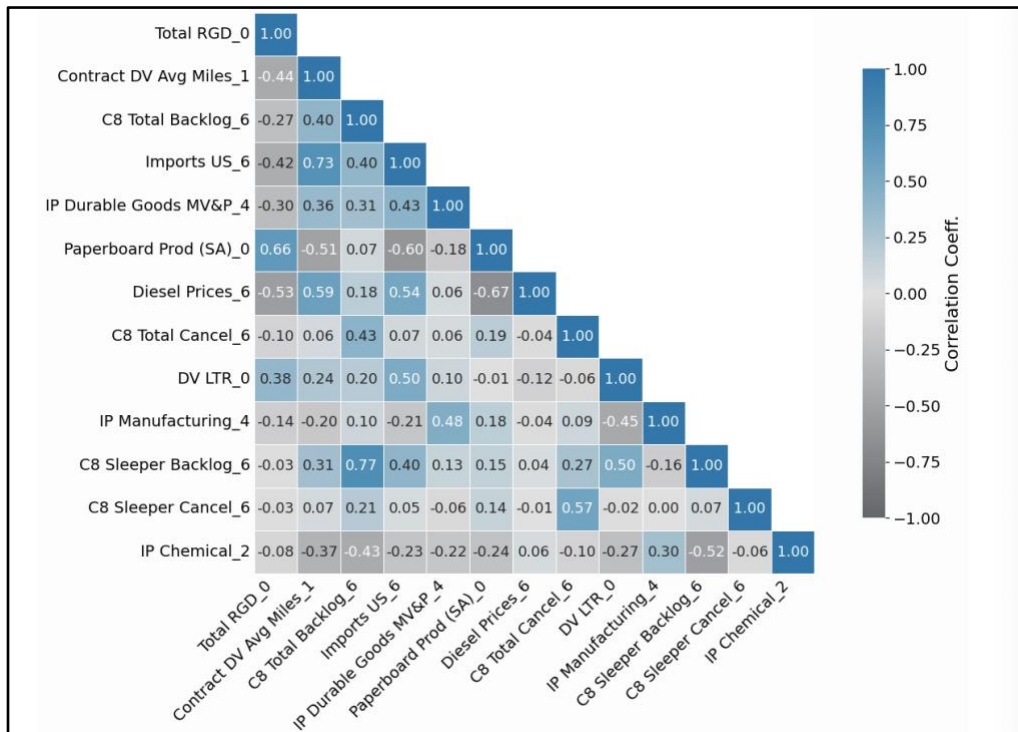


Figure 2. Correlation Matrix of Filtered Lagged Predictors in the Dry Van Expansion Model

After applying the correlation filtering and finalizing the feature set, the dataset is split using an 80/20 train-test split to evaluate the model's predictive performance. A larger test set is used to ensure that both classes are sufficiently represented in the out-of-sample data.

The model demonstrates strong performance in the training data, with an Area Under the Curve (AUC) of 0.955. The AUC measures the model's ability to correctly distinguish between periods that lead to expansion and those that do not across all possible classification thresholds. An AUC of 0.955 indicates that, given a random pair of observations (one that leads to expansion and one that does not), the model assigns a higher probability to the expansion case approximately 95.5% of the time.

When evaluated on the test dataset, the model achieves an AUC of 0.906, indicating strong discriminatory ability in distinguishing between expansion and non-expansion periods in out-of-sample data. However, this difference between training and test performance should be interpreted with caution, as it may reflect sample size limitations or differences in class distribution rather than consistent model generalization.

Examining the statistical significance of the predictors, several variables exhibited meaningful relationships with the probability of a Dry Van Expansion. Industrial Production Chemical (lag 2 months), Class 8 Total Cancel (lag 6 months), and Contractual DV Average Miles (lag 1 month) are statistically significant ($p < 0.05$). Class 8 Total Backlog (lag 6 months) and IP Durable Goods Motor Vehicles and Parts (lag 4 months) displayed a marginal level of significance ($p < 0.1$). These results suggest that changes in the number of truck orders and production levels influence freight pricing and carrier capacity adjustments in the months leading up to expansionary conditions in the market.

5.1.2 Temperature Control Expansion Model Results

To evaluate the drivers of expansion in the Temperature Control market, we apply the same Logistic Regression framework used in the Dry Van model. The model achieves a training AUC of 0.926, indicating that the model is able to reasonably distinguish between periods that would lead to expansion and those that would not within the training dataset. When evaluated on the out-of-sample test dataset, the model produced a testing AUC of 0.603, suggesting that while the model retains some predictive signal, its out-of-sample performance is weaker compared to the Dry Van model.

This difference in performance may reflect greater volatility and weaker leading relationships in the Temperature Control market, as well as differences in the timing of key indicators across modes. While some predictive signal remains, the model is less reliable for forecasting expansion in Temperature Control than it is for Dry Van.

In terms of statistical significance, Class 8 Total Backlog (lag 6 months) shows the strongest relationship with the probability of expansion, with a very strong p-value (0.005). Total RGD (lag 0 months) exhibits the strongest positive coefficient, suggesting a directional relationship with expansion; however, these coefficients should be interpreted as relative contributions to the model rather than precise causal effects.

Figure 3 expands on these results by showing the relative importance of all predictors based on standardized coefficients. These coefficients indicate the direction and relative magnitude of each variable's influence on the probability of expansion, but do not imply exact quantitative impact in real-world units.

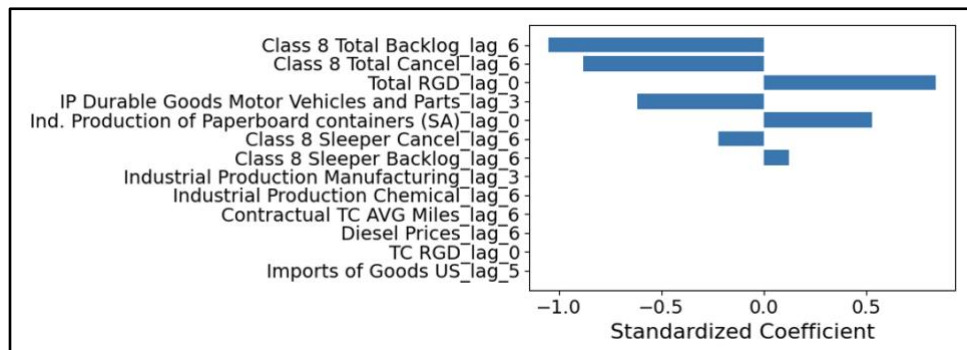


Figure 3. Predictive Importance of Lagged Indicators in the Temperature Control Expansion Model

5.1.3 Flatbed Expansion Model Results

Unlike the Dry Van and Temperature Control models, we could not estimate a Flatbed Expansion model. When constructing the forward-looking target variable, we found no observed phase transitions in the available Flatbed dataset using the current parameters. Logistic Regression requires variation in the dependent variable to estimate event probabilities, but no expansion shifts occurred in this data. As a result, we were unable to train or evaluate the model, and no statistical results are reported for Flatbed expansion.

5.2 Contraction Model Results

The intention of developing the Contraction models is to analyze the predictive accuracy of the current architecture of the model by testing it on a known phase shift. This approach also allows C.H. Robinson to use the model to anticipate future contractions while the market remains in an expansion phase.

5.2.1 Dry Van Contraction Results

To evaluate the drivers of Contraction in the Dry Van market, we apply the same Logistic Regression framework used in the Expansion model, adjusting the dependent variable to capture transitions into contractionary periods. The dataset is restricted to the 2012–2022 period to capture the full market cycle leading into the most recent downturn.

The model demonstrates strong predictive capability within the training dataset, achieving a training AUC of 0.955. When evaluated on the out-of-sample test dataset, the model produces a testing AUC of 0.963, indicating strong predictive performance when applied to unseen observations.

As seen in Table 2, two variables are statistically significant at the 5% level: Class 8 Total Backlog (lag 6 months) and Imports of Goods to California (lag 0 months). Class 8 Total Cancel (lag 6 months) is moderately significant.

	coef	p_value	CI_low	CI_high	odds_ratio	OR_CI_low	OR_CI_high
Industrial Production Chemical_lag_2	-0.7081	0.0012	-1.1352	-0.2809	0.4926	0.3214	0.7551
Class 8 Total Cancel_lag_6	-0.0043	0.0086	-0.0075	-0.0011	0.9957	0.9925	0.9989
Contractual DV AVG Miles_lag_1	-0.0709	0.0280	-0.1341	-0.0077	0.9316	0.8745	0.9924
Class 8 Total Backlog_lag_6	-0.0000	0.0663	-0.0000	0.0000	1.0000	1.0000	1.0000
IP Durable Goods Motor Vehicles and Parts_lag_4	-0.1556	0.0757	-0.3273	0.0161	0.8559	0.7209	1.0162
Imports of Goods US_lag_6	-0.0000	0.1169	-0.0001	0.0000	1.0000	0.9999	1.0000
Class 8 Sleeper Cancel_lag_6	-0.0437	0.1801	-0.1077	0.0202	0.9572	0.8979	1.0204
Total RGD_lag_0	1.8510	0.3529	-2.0541	5.7561	6.3663	0.1282	316.1234
DV LTR_lag_0	0.2145	0.6805	-0.8064	1.2355	1.2393	0.4464	3.4400

Table 2. Inference Results for Dry Van Contraction Model

5.2.2 Temperature Control Contraction Results

To evaluate Contraction in the Temperature Control market, we apply the same Logistic Regression framework used in the Expansion model, adjusting the dependent variable to capture transitions into contractionary periods. The model achieves a training AUC of 0.902 and a testing AUC of 0.959, indicating strong predictive capability when applied to unseen observations.

In terms of statistical significance, no feature is strongly significant (p-value < 0.05) for this model, though Industrial Production of Paperboard Containers (lag 6 months) and Total RGD (lag 0 months) are moderately significant (p-values 0.106 & 0.167)

5.2.3 Flatbed Contraction Results

Lastly, we apply the same logic to the Flatbed market. Unlike with the Expansion model, we were able to get results, as most observations in the Flatbed dataset are from contractionary periods. The model achieves a train AUC of 0.963 and test AUC of 0.967, meaning the model is able to accurately predict on data it had not seen before just as well as data it was trained on.

There are several statistically significant variables in this model, with Industrial Production of Chemicals (lag 6 months), Class 8 Total Cancel (lag 5 months), Class 8 Sleeper Cancel (lag 6 months), and Industrial Production of Manufacturing (lag 6 months) all having p-values below 0.05.

5.3 Model Prediction Results

To evaluate the model’s predictive capability, we generate an out-of-sample forecast using the most recent observation in the dataset. The model estimates the probability that the market regime will shift in three months, corresponding to the defined forecast horizon.

For the Dry Van Expansion model, the most recent forecast (as of March 2026) indicates an 83.74% probability of a regime shift in three months, suggesting a relatively high likelihood of an expansionary transition in the near term. As shown in Figure 4, the most recent portion of the probability timeline remains well above the 50% threshold, indicating that the Dry Van market is likely to enter an expansionary phase in the near term.

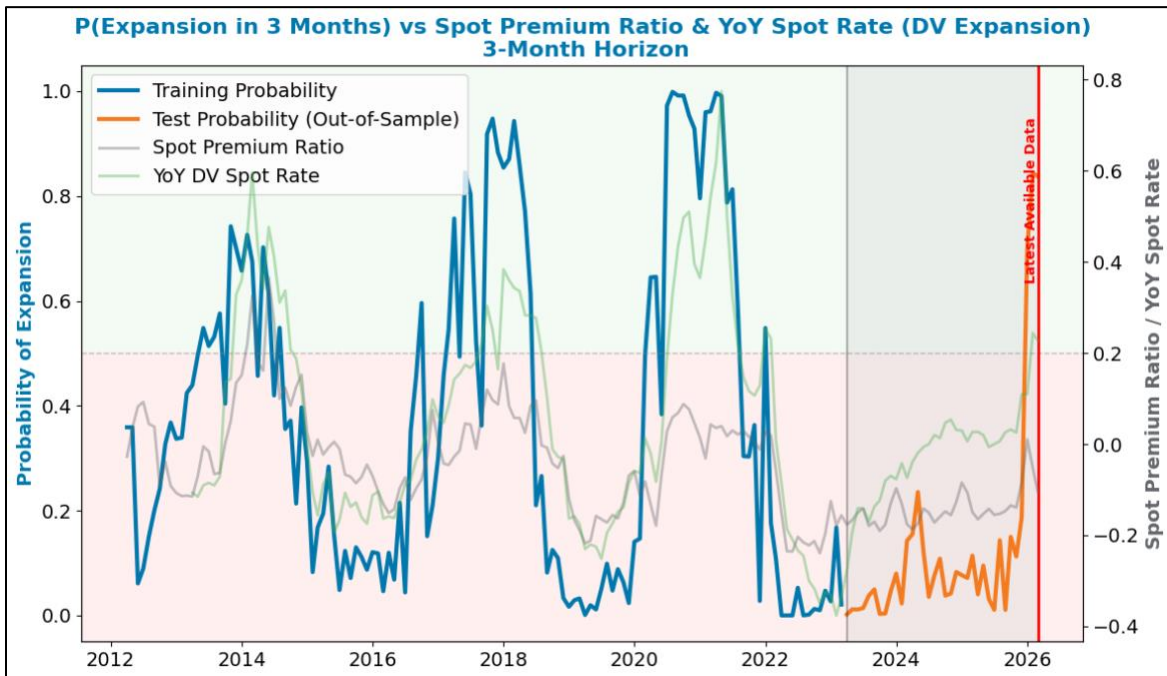


Figure 4. Dry Van Expansion Probability vs. Spot Premium Ratio & YoY Spot Rate (Three Month Forecast Horizon)

Applying the same framework to the Temperature Control Expansion model, the most recent forecast indicates a 40.50% probability of a regime shift as of March 2026, suggesting that the Temperature Control market is unlikely to experience an expansionary transition in the near term.

For the Contraction models, which are trained on data through February 2022 to validate against a known historical outcome, the Dry Van model estimated a 99.89% probability of contraction in May 2022, the Temperature Control model estimated 61.87%, and the Flatbed model estimated 7.51%. The

Dry Van result demonstrates strong directional accuracy, correctly anticipating the onset of the most recent contractionary period with high confidence.

Table 3 summarizes the logistic regression coefficients and significance levels across all five models. Coefficients indicate the direction and relative strength of each predictor, while asterisks denote statistical significance. Positive values suggest a higher likelihood of expansion or contraction, depending on the model, while negative values indicate the opposite. Pseudo R² indicates model fit in logistic regression (higher values suggest better fit). For example, in the Dry Van Expansion model, the log-odds of a market shift start at a baseline intercept of 165.24 and decrease by 0.004 for every unit increase in Class 8 Total Canceled orders (lag 6 months), indicating that higher cancellation rates significantly reduce the likelihood of entering an expansion phase.

Independent Variable	Lag	DV Expand	DV Contract	TC Expand	TC Contract	FB Contract
Intercept (β_0)	—	165.24***	-44.17	-26.24**	-76.59	-377.54**
Class 8 Orders						
Class 8 Total Backlog	6	-0.00**	0.00***	-0.00***		0.00
Class 8 Total Cancel	6	-0.004***	0.005*	-0.002**		
Class 8 Total Cancel	5					0.009**
Class 8 Sleeper Backlog	6			-0.030	-0.00	
Class 8 Sleeper Cancel	4		0.032			
Class 8 Sleeper Cancel	6	-0.044		-0.030		0.060**
Industrial Production						
IP Chemical	2	-0.695***				
IP Chemical	6		0.632			1.420***
IP Durable Goods MV&P	0		0.130			
IP Durable Goods MV&P	1					0.209
IP Durable Goods MV&P	3			-0.093*		
IP Durable Goods MV&P	4	-0.156*				
IP Manufacturing	6					2.211**
Paperboard Production (SA)	0		-0.239	0.358**		
Paperboard Production (SA)	6				0.781	
Freight Metrics						
DV LTR	0	0.214				
FB LTR	2					-0.249
Contractual DV AVG Miles	1	-0.071**				
Total RGD	0	1.851		2.493**	-2.870	
Trade & Imports						
Imports of Goods US	0					-0.00
Imports of Goods US	6	-0.00				
Imports of Goods California	0		-0.001***			
Diesel Prices	0					0.738
Pseudo R²	—	0.60	0.68	0.50	0.58	0.68

* p < 0.10 ** p < 0.05 *** p < 0.01 Blank = variable not selected by model Contraction models trained on data through Feb 2022; P(Contraction) reflects forecast as of that date.

Table 3. Logistic Regression Coefficient Table Across Equipment Types and Market Regimes

5.4 Multi-Horizon Forecast

To build a more robust forecasting solution, we developed a multi-horizon forecasting model for three to six months that assesses the likelihood that the Dry Van market will shift into an expansionary phase over a given range of months.

The predicted probabilities across forecast horizons are shown in Figure 5. Using the same logic as the above expansionary models, we predicted the following probabilities of a shift into Expansion.

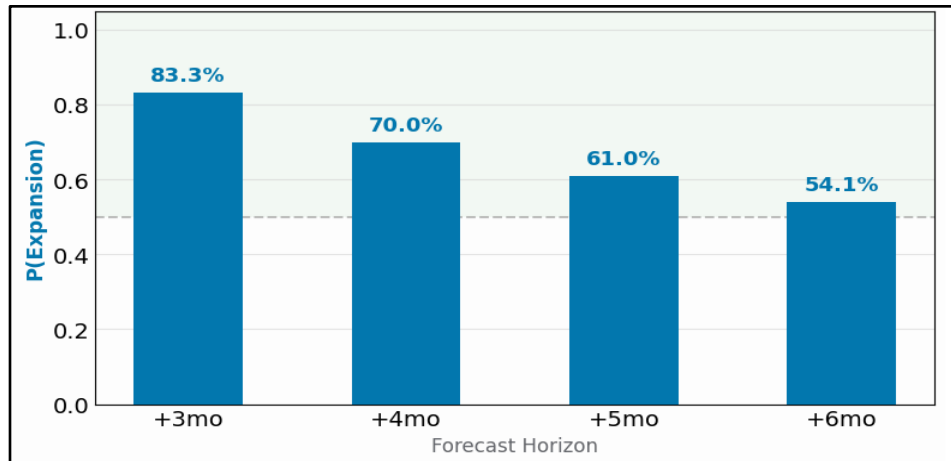


Figure 5. Dry Van Expansion Multi-Horizon Forecast Over Six Months

5.5 Limitations

While these models provide a structured framework for predicting truckload market cycle transitions, a few limitations remain. First, the dataset lacks the historical depth required for high-level significance. The dataset provided goes back to 2012, with 171 data points: 62 in expansion and 109 in contraction. This limited sample includes relatively few complete market cycles, which reduces statistical power and makes it difficult to estimate stable and statistically significant relationships.

Second, the COVID-19 pandemic introduced significant structural changes to the truckload market. The extreme and prolonged rate increases, followed by extended deflation, created atypical market behavior, particularly during the unusually long Trough Recovery phase. As a result, relationships observed in the pre-COVID period do not consistently hold in the COVID and post-COVID periods, reducing the model's ability to generalize across time.

These structural shifts highlight a key limitation: the model assumes relatively stable relationships between indicators and market outcomes, which may not hold in periods of disruption. As a result, model performance may vary depending on the underlying market regime.

6. Recommendations

This research substantiates that freight market cycle transitions exhibit discernible patterns identifiable through the integration of exogenous macroeconomic indicators and endogenous pricing signals. By evaluating multiple equipment types and market regimes, this study demonstrates that predictive modeling approaches can successfully capture the non-linear shifts in market conditions. These findings suggest that C.H. Robinson can transition toward a data-driven, proactive operational approach by deploying these models into an iterative, real-time dashboard. However, the observed variance in performance metrics across different equipment types and regimes indicates a high degree of sensitivity to local market variables. This necessitates a targeted deployment strategy: the forecasting framework should be treated as a specialized tool optimized for high-reliability segments where signal-to-noise ratios are most favorable. Doing so can improve gross margin performance, increase market responsiveness, and support better decision-making during market volatility.

6.1 Management Recommendations

This study provides several actionable insights for C.H. Robinson, particularly in how freight market cycle signals can be used to inform strategic decision-making. The results indicate that while market

transitions can be partially anticipated using macroeconomic and pricing indicators, predictive performance varies across equipment types and market conditions. As a result, these insights should be applied selectively, focusing on the contexts in which the models demonstrate the strongest predictive power.

The analysis highlights that C.H. Robinson should prioritize the high-signal indicators when making decisions related to capacity planning, pricing, and carrier engagement, rather than relying on a broad set of variables. By focusing on the most predictive signals, the firm can improve the timing of key decisions and reduce exposure to unfavorable rate environments, ultimately protecting margins during periods of volatility.

Given the moderate predictive strength of the models and the presence of structural shifts in the market, such as those observed during the COVID-19 period, model outputs should be used as directional inputs rather than definitive decision rules. Combining model-driven insights with industry expertise and real-time market knowledge will enable more balanced and informed decision-making, reducing the risk of overreliance on imperfect signals.

Finally, integrating these predictive insights into existing strategic planning processes can enhance organizational responsiveness to market changes. Incorporating forecasts into monthly or quarterly planning cycles can support procurement strategies, pricing decisions, and carrier management efforts. Overall, the findings suggest that while forecasting models are not universally reliable, they can serve as valuable decision-support tools when applied thoughtfully and in the appropriate contexts.

6.2 Future Work

To build on the study's promising results, future frameworks should expand beyond national-level variables to include regional freight dynamics. Truckload markets are inherently localized, driven by regional industrial cycles and seasonal patterns. Incorporating lane-level data of both macroeconomic variables and pricing data would allow the model to capture these specific supply-demand fluctuations, leading to more precise forecasting.

Additionally, the criteria used to define Flatbed equipment cycles should be re-evaluated. The failure of the Expansion model to produce results stems from a lack of relevant training phases, which are currently defined by rules established from Dry Van. This suggests that Flatbed dynamics are sufficiently unique to justify their own distinct framework, rather than being grouped with Dry Van and Temperature Control.

Future research should focus on expanding the dataset to encompass a broader historical horizon and additional market cycles. Extending the time series could improve statistical reliability and allow for more robust validation across varying economic climates, specifically accounting for structural shifts like those triggered by the COVID-19 pandemic. Crucially, further analysis is required to determine whether the current post-pandemic environment constitutes a 'new normal' or a temporary anomaly. Identifying whether the current cycle is behaving atypically due to its unique origins—or if it represents a fundamental resetting of market dynamics—remains a vital area for future inquiry.

Appendix: Additional Model Figures

Additional model figures, including predictive importance charts and probability timelines across all models, are available [here](#).

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