Defining and Forecasting Full Truckload Market Cycles

by

Sarah Roman
Supply Chain and Information Systems, B.S., The Pennsylvania State University, 2020

and

Wirinratch Kirirak
Economics, B.E., Thammasat University, 2022

SUBMITTED TO THE PROGRAM IN SUPPLY CHAIN MANAGEMENT
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF APPLIED SCIENCE IN SUPPLY CHAIN MANAGEMENT
AT THE
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2025

Signature of Author: ______________________________
Department of Supply Chain Management
May 9, 2025

Signature of Author: ______________________________
Department of Supply Chain Management
May 9, 2025

Certified by: ______________________________
Dr. Chris Caplice
Executive Director of MIT CTL
Capstone Advisor

Certified by: ______________________________
Dr. Angela Acocella
Research Scientist
Capstone Advisor

Accepted by: ______________________________
Prof. Yossi Sheffi
Director, Center for Transportation and Logistics
Elisha Gray II Professor of Engineering Systems
Professor, Civil and Environmental Engineering

Defining and Forecasting Full Truckload Market Cycles

by
Sarah Roman
and
Wirinratch Kirirak

Submitted to the Program in Supply Chain Management
on May 9, 2025 in Partial Fulfillment of the
Requirements for the Degree of Master of Applied Science in Supply Chain Management

ABSTRACT

The U.S. full dry-van truckload (FTL) industry serves as a primary channel through which goods move across the country, forming the essential backbone for all product categories and commodity groups. Following the Motor Carrier Act of 1980, the truckload industry was deregulated and became increasingly influenced by market dynamics. Since 2012, three distinct market cycles have been observed, each initiated by a significant shock or catalyst. These include the implementation of new Hours of Service regulations in 2013, the introduction of Electronic Logging Device (ELD) mandates in 2016, and the onset of the COVID-19 pandemic in 2020. While practitioners of the trucking industry have long attempted to predict these cycles, an industry-driven definition and standardized way of predicting upcoming cycles has yet to be written. This research first defines an industry-driven, four-phase definition of the truckload market cycle using insights from expert interviews and a widespread survey. Driven by these insights, this study uses time-series econometric model which is Vector Autoregression (VAR) to predict the upcoming two years of spot and contract rates based on independent variables. In conclusion, our findings identify the key variables that most significantly influence truckload market cycle projections, establish the optimal lag structure, and provide forecasts in both the short-term and long-term.

Capstone Advisor: Dr. Chris Caplice
Title: Executive Director of the Massachusetts Institute of Technology's Center for Transportation & Logistics (CTL)

Capstone Advisor: Dr. Angela Acocella
Title: Research Scientist

ACKNOWLEDGMENTS

We are grateful to our faculty advisors, Dr. Chris Caplice and Dr. Angi Acocella, for their unwavering support and guidance. We extend our sincere appreciation to our sponsor company, C.H. Robinson, for their partnership, provision of data, and insightful recommendations that shaped the direction of this work. Finally, we thank the industry practitioners who contributed their time and expertise to ensure this research provides meaningful value to the broader trucking industry.

Sarah extends her heartfelt gratitude to her family, friends, fiancé, and puppies for their unwavering support, encouragement, and presence throughout the course of this project. She also extends her genuine gratitude to Wirinratch for ten unforgettable months filled with laughter, a few tears, unwavering dedication, and a friendship that has meant more than words can express.

Wirinratch Kirirak: I would like to thank my parents for unwavering support throughout life and to my big brother, Phatchara Kirirak—I would never be who I am today without you. I'm also grateful to Angi for her encouragement and for helping us navigate challenges with her sharp instincts with data, and to Chris for showing us how to approach problems with purpose and uphold high standards. Also, thank you to Pam for guiding us throughout the writing. Lastly, to my amazing capstone partner, Sarah—thank you for your dedication and partnership. We've shared laughs and worked through tough moments together, and now we did it!

TABLE OF CONTENTS

FIGURES AND TABLES

Figures

Tables

1 Introduction

In 2023, the United States transportation industry was valued at $1.5 trillion, with the full truckload (FTL) sector accounting for $408.7 billion (Acar et al., 2024), representing 5.5% and 1.5% of GDP, respectively (Bureau of Economic Analysis U.S. Department of Commerce, 2024).

The U.S. dry van FTL market operates in a continuous balancing act between truck capacity (supply) and freight demand, leading to a cyclical pattern that shifts between tight and soft market conditions. In a tight market, freight demand exceeds available capacity, whereas in a soft market, truck capacity exceeds demand (Acocella et al., 2020). Since 2008, multiple organizations, including Pickett Research and RXO, Inc. (formerly Coyote Logistics) have tracked these cycles. A shipper is the organization that sells a product that needs to be shipped, while a carrier is the organization that physically transports the shipment by truck. When shippers anticipate recurring shipments along a specific transportation lane (a route from a single origin to a single destination), they often enter into a contract with a carrier to lock in a fixed rate for a designated period of time. Contracts are only binding on price, not the quantity shipped or capacity provided (McBride, 2024). When shippers have low volume, infrequent shipments, or must transport product outside of their contracted lanes or a contracted carrier is unable to accept a load, shippers look to the spot market to secure capacity (Clarksons, n.d.). During tight markets, spot prices rise, causing shippers to pay more for capacity outside of their contracts. Soft markets equate to carriers having excess capacity, driving down spot prices (RXO, n.d.-a). Third-party brokerage firms, such as C.H. Robinson, sometimes serve as intermediaries for these contractual relationships and match shipper demand with carrier transportation supply (Williams, 2025).

As shown in Figure 1, ACT Research and C.H. Robinson currently define the truckload market cycle using four phases: Under Supply, Late Cycle: Balance Recovery, Over Supply, and Early Cycle: Balance Recovery. Under Supply is characterized by an abundance in freight demand and capacity shortage, leading to increasing spot rates and a need for capacity expansion. With shippers' demand exceeding truckload capacity, this leads to a tight market. The Late Cycle: Balance Recovery is characterized by a reduction in freight demand or increase in capacity, causing spot rates to decline and indicating that the market is loosening. The Over

Supply phase, also known as a soft market (Acocella et al., 2020), occurs when truckload capacity exceeds shippers' demand. During this phase, spot prices typically fall to their lowest point, while contract prices tend to lag behind, adjusting after approximately six months. Finally, Early Cycle: Balance Recovery is characterized by an increase in freight demand and tightened capacity, driving spot price to increase, but not peak. The market is finding equilibrium, rebalancing a state of excess supply in the Over Supply phase. At this time, the truckload business is reentering a tight market (ACT Research, 2023).

Figure 1: Truckload Market Cycle (ACT Research, 2023 and graphic by C.H. Robinson)

In addition to ACT and CHR's four-phase truckload market cycle definition, RXO, a transportation solutions organization, defines the cycle using seven phases. Phase one, Equilibrium, represents a balanced state in which carrier capacity aligns with shipper demand. Phase two, Market Inflation, is characterized by rising spot rates that exceed contract rates, prompting an influx of carrier capacity as operators respond to increased demand. Phase three, the Inflationary Peak, is marked by elevated spot rates and low tender acceptance rates, signaling that sufficient capacity has entered the market and initiating the downturn of the cycle. Phase four, Market Deflation, is characterized by declining spot rates and the beginning of capacity exiting the market. During this period, contract rates may continue to rise as they lag in responding to the prior peak in spot rates. Phase five, the Deflationary Trough, occurs when declining rates from the prior phase have pushed capacity out of the market. This would cause an imbalance where demand exceeds available capacity, often leading to a rebound in spot rates.

Phase six, referred to as 2nd Market Inflation, is characterized by rising rates even though the market has not yet begun to feel the effects of the tightening capacity. Finally, phase seven marks the Return to Equilibrium, where carrier capacity and shipper demand are once again balanced, signaling the conclusion of the current cycle and the onset of a new one (RXO, n.d.-b).

While ACT and C.H. Robinson define the truckload market cycle using a four-phase model and RXO adopts a seven-phase framework, both approaches fundamentally describe the same cyclical dynamics. Each model illustrates that rising rates are indicative of a tightening market in which capacity grows to meet increased demand. Conversely, both acknowledge that as capacity eventually supersedes demand, rates decline, prompting an exit of excess capacity from the market. Regardless of the number of phases, both definitions highlight the cyclical nature of the market as it fluctuates and consistently works to reestablish equilibrium.

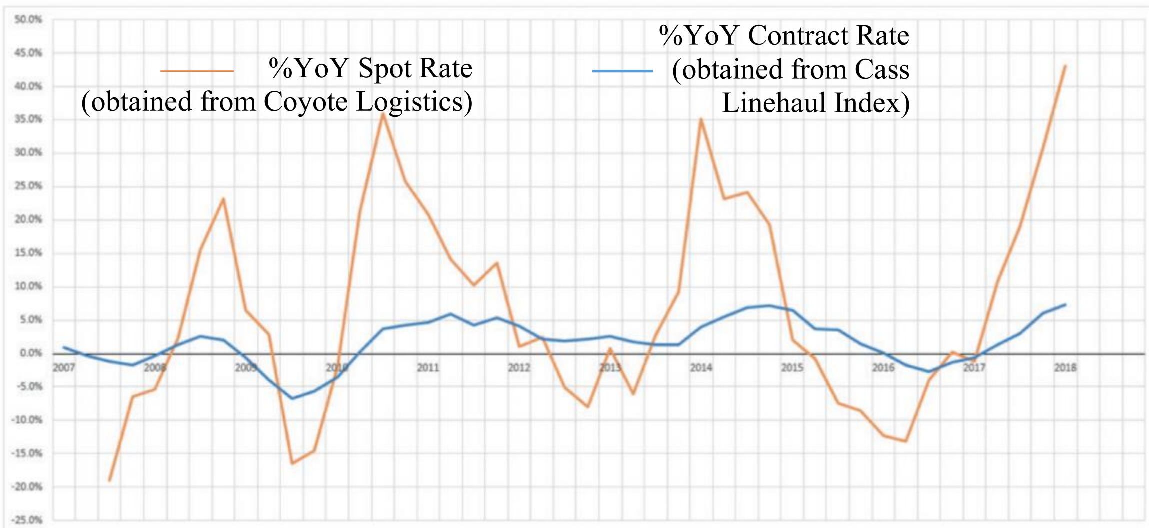
Despite the presence of multiple frameworks, a standardized methodology for identifying the precise timing of phase transitions or the onset of a new truckload market cycle has yet to be established. As a result, the timing of truckload market cycles is not fully understood. Unlike the predictable cadence of seasonal patterns (e.g., weekends, U.S. holidays), cycles in the full-truckload industry do not follow such regimented patterns. Freight demand is dependent upon other industries including manufacturing, agriculture, retail, and real estate. To help navigate shifting demand patterns, the industry needs a reliable resource to assess market performance.

Before addressing the research question, it is important to first understand the historical context of the truckload market cycles, which is outlined in the following paragraphs. A key turning point was the Motor Carrier Act of 1980 which significantly reduced government regulation of the trucking industry, eliminating many restrictions on carriers and making it easier for new entrants to join the market. Ultimately, this encouraged price competition among carriers (U.S. Government Accountability Office, 1981).

Chris Pickett, formerly of Coyote Logistics and founder of Pickett Research, LLC, was among the first to introduce the concept of truckload business cycles, identifying the existence of cycles from 2007 to 2018. Figure 2 highlights spot and contract rates trends in the U.S. long-haul, dry van, FTL market derived from Coyote Logistics Research. The orange line represents the year-over-year (YoY) change in spot rates, while the blue line reflects YoY contract rate changes based on the Cass Truckload Linehaul Index, which is derived from freight invoice data processed by Cass Information Systems, a freight audit and payment firm (Cass Information

System, n.d.). Because an estimated 70–80% of FTL transactions are contract-based (BlueGrace Logistics, 2022), the Cass Truckload Linehaul Index serves as a reliable indicator for tracking contract rate trends in the market.

Figure 2: Truckload Market Cycles (2008-2018) (Pickett, 2018)



After acquiring Coyote Logistics, RXO continued tracking the truckload market cycle, extending the analysis period to 2025. Figure 3, produced by RXO, illustrates YoY changes in truckload spot and contract rates from 2017 to 2025. The spot rate (green line) is sourced from RXO, while the contract rate (blue line) is derived from the Cass Truckload Linehaul Index, consistent with the methodology used in Pickett's work.

Figure 3: Truckload Market Cycles (2007-2025) (RXO, 2025)

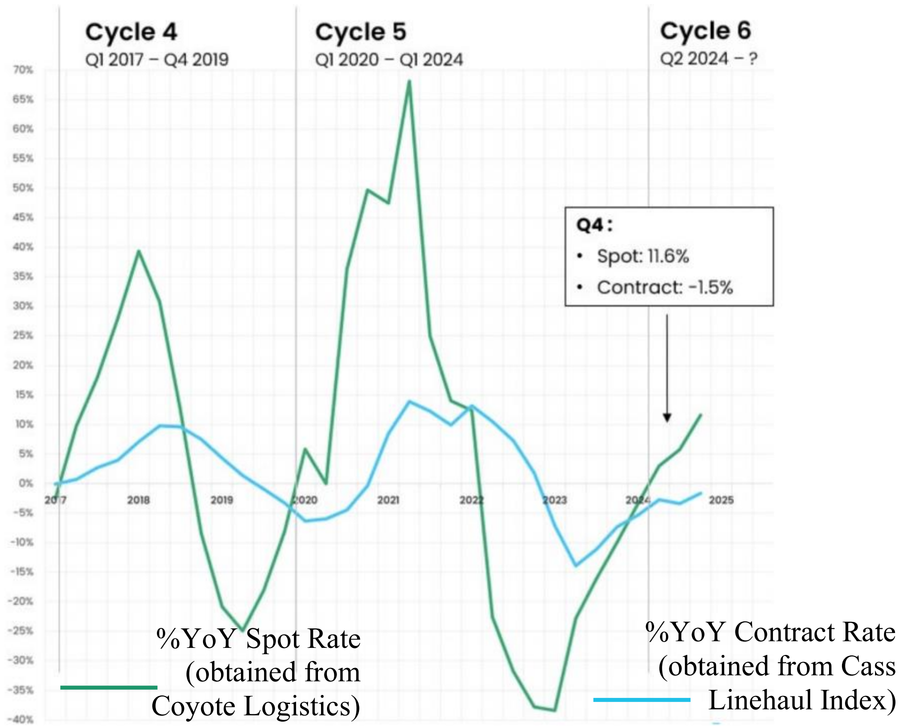


Figure 2 and Figure 3 reveal several key similarities. Spot rates exhibit significantly greater volatility than contract rates across both charts. Spot rates also tend to rise earlier and more sharply than contract rates, then decline more quickly and steeply during downturns, suggesting that contract rates follow spot rate trends with more stability. Across both figures, the truckload market displays a pronounced cyclical pattern.

Figure 2 shows that spot rate is highly volatile, with YoY changes ranging from approximately -25% to +35%. In contrast, contract rate, sourced from the Cass Truckload Linehaul Index, fluctuates within a much narrower band of approximately -5% to +10% YoY. The cycles during this time period (2008 – 2017) are relatively short, typically lasting two to three years, when compared to Figure 3. In contrast, RXO (Figure 3) highlights a shift in both volatility and cycle duration, particularly after 2020. Spot rates in this chart exhibit a much sharper rise and fall, ranging from -35% to as high as +65% YoY. Although contract rate also shows more movement than in the earlier period, they continue to lag behind spot rates. Notably, the cycles in Figure 3 extend over a longer duration of about four years.

These charts demonstrate that the tracking of truckload business cycles predates 2012. However, due to data limitations, our analysis spans 2012 to 2025, a period that encompasses three complete truckload market cycles, as illustrated in Figure 4. We obtained long-haul, dry van, FTL rates from DAT Freight & Analytics, sourced from over 200 shippers in the DAT iQ consortium. Specifically, spot rates represent one-time shipper 'buy' transactions, while contract rates are derived from longer-term shipper-to-carrier agreements based on data from thousands of freight invoices (DAT, 2025).

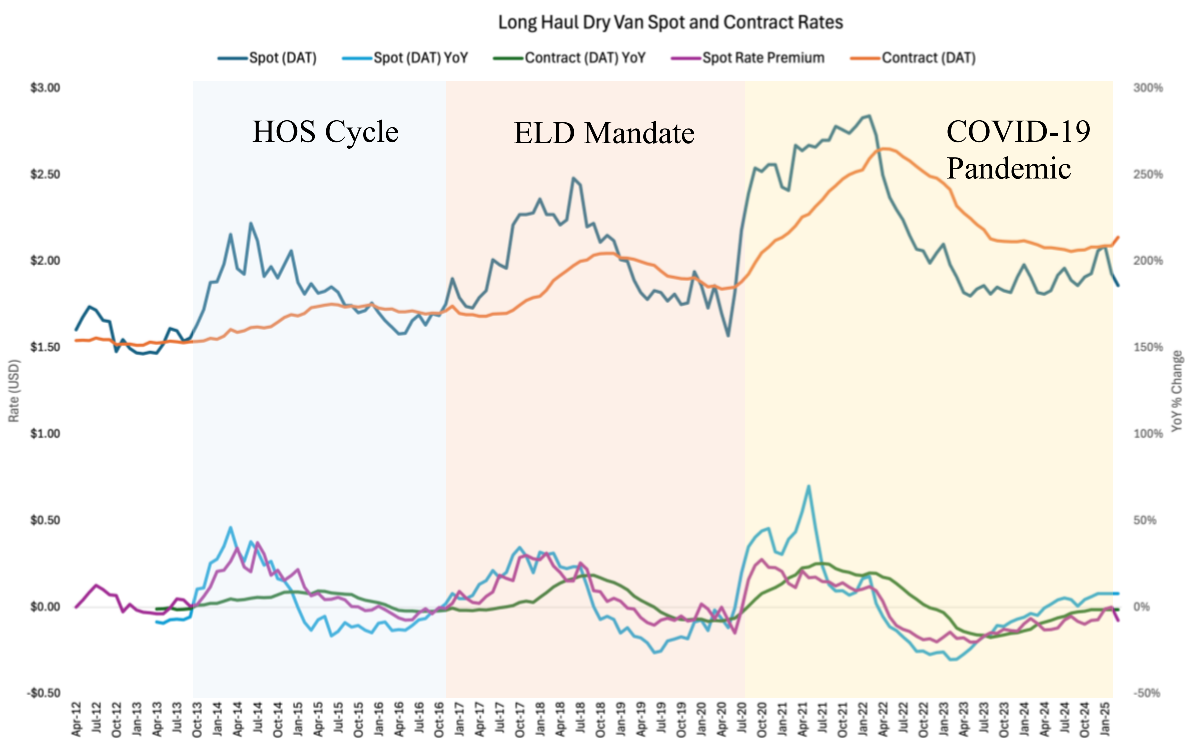
Figure 4 displays long-haul dry van FTL spot and contract rates in both U.S. dollars and YoY percentage changes. It also includes the spot premium ratio, defined as the percentage difference between spot and contract rates and given by $\text{Spot Premium Ratio} = \frac{\text{Spot Rate} - \text{Contract Rate}}{\text{Contract Rate}}$. The first cycle began in Q3 2013 and concluded in Q1 2017, spanning 15 consecutive quarters. This period was primarily influenced by the introduction of the new Hours of Service (HOS) regulations, which reduced the maximum average work week for truck drivers from 82 to 70 hours (Bowman, 2013). The decline in available capacity contributed to increases in both spot and contract rates. This cycle reached a peak spot rate of $2.22 and bottomed at $1.58, yielding a peak-to-trough amplitude of $0.64.

The second cycle began in Q1 2017 and was defined in part by the implementation of the Electronic Logging Device (ELD) mandate, a federal regulation introduced by the Federal Motor Carrier Safety Administration (FMCSA). This mandate required commercial motor vehicle drivers to electronically record their HOS in an effort to enhance road safety and improve regulatory compliance (Federal Motor Carrier Safety Administration, 2017). The costs associated with ELD installation and reduction in driving capacity due to stricter compliance, contributed to rising spot and contract rates (Miller et al., 2020). During this cycle, the spot market peaked at $2.44 before declining to a trough of $1.57, resulting in a peak-to-trough amplitude of $0.87. The cycle concluded in Q1 2020, spanning a total of 13 quarters.

The third cycle emerged in response to the COVID-19 pandemic. Spot rate experienced an initial sharp decline as widespread lockdowns disrupted economic activity. However, beginning around Q2 2020, rates rebounded rapidly, fueled by a surge in demand driven by government stimulus payments and the gradual return of commercial activity. During this cycle, spot rates peaked at $2.84 and reached a trough of $1.80, resulting in a peak-to-trough amplitude of $1.04.

Figure 4 illustrates three distinct truckload market cycles spanning from April 2012 to March 2025. The top two lines depict the raw spot and contract rates, aligned with the left vertical axis (rates in USD). The lower three lines show the percent YoY change in spot and contract rates, along with the spot premium ratio. The peaks and troughs in both the raw and YoY data tend to mimic one another's movements. Similar to the patterns observed in Pickett's work and RXO's analysis, DAT data reflects clear, cyclical behavior in spot and contract rates. In each case, contract rate consistently lags behind spot rate but follows a similar directional pattern. However, differing cycle definitions and frameworks contribute to variations in how and when cycle transitions are identified.

Figure 4: DAT Spot vs. Contract Rates Over Time



1.1 Problem Statement

The truckload industry does not reliably forecast future cycles due to the unpredictable nature of these fluctuations. Without a method to anticipate cycle shifts in the current marketplace, the FTL industry, including shippers, carriers, and brokers, must react immediately to changing conditions. In partnership with our sponsor, C.H. Robinson, this capstone:

1) Identifies two dependent variables, spot and contract rate, that represent the truckload industry's business cycles.
2) Defines the phases of the truckload market cycle using these dependent variables.
3) Determines the independent variables that have historically influenced the dependent variables.
4) Forecasts the timing of future phases/cycles based on these factors.

This research is intended for industry-wide use to enhance the overall efficiency and effectiveness of the FTL industry. It recommends an industry-informed definition of the FTL business cycle and identifies key independent variables that can significantly predict these cycles. Ultimately, this analysis forecasts the timing of shifts within and between the business cycle to help stakeholders prepare for fluctuations in trucking capacity and demand, focusing exclusively on the U.S. truckload industry.

These insights benefit the entire FTL industry by enabling organizations to quickly adjust their tactical and strategic plans in response to changes in the external factors identified. The remainder of this capstone is structured with a State of the Practice, Methodology, Results, Discussion, and Conclusion.

2 State of the Practice

Our research addresses a critical issue faced by the truckload industry, namely the absence of a comprehensive definition of the truckload business cycle and a model to predict the duration of future cycles. Currently, industry experts across various organizations rely on many metrics to understand the truckload business cycle, resulting in a fragmented and inconsistent definition.

In the following sections, we discuss the current methods used to track the truckload business cycle (Section 2.1) and the challenges associated with the existing approaches (Section 2.2).

2.1 Current Industry Practices

Today's truckload business market employs a variety of practices and methods to understand and predict industry business cycles. During interviews with twenty industry experts, more than thirty metrics were identified as primary sources of insight. We synthesized the experts' definitions of the truckload business cycle into four key groups: spot and contract rates, tender rejection rates, supply and demand, and financial performance.

Our interviews suggest that many industry practitioners assess the truckload business cycle using key rate-based metrics, most notably spot and contract rates, along with the spot premium ratio. Freight market platforms such as DAT Freight & Analytics, Truckstop.com, and FreightWaves SONAR each provide a range of tools, including real-time spot rate data, contract rate insights, market indices, and historical pricing trends, though offerings vary by provider. An interviewed executive with a major technology firm explained that the spot premium ratio serves as an indicator of where the truckload business cycle stands. Apart from the spot premium ratio, an alternative way to look at the difference between spot and contract rates is to consider the spread between them. A widening spread suggests an imbalance between freight demand and truck capacity, while a narrowing spread indicates that supply and demand are approaching equilibrium.

Spot and contract rates are widely viewed as key indicators of market conditions in the transportation industry. Eleven interviewed professionals believe that a positive YoY spot rate percent change indicates a tight market, while a negative YoY percent change suggests a loose market. A senior leader at a freight brokerage organization illustrated this concept using the Pickett Line published by Pickett Research, LLC, which visualizes spot rate changes on a YoY basis. Another widely accepted view among our interviewed experts is that market shifts occur only when a sustained positive or negative percent change in spot rates is observed, often on a YoY basis. However, a few interviewees also monitor week-over-week or month-over-month spot rate dynamics. While short-term fluctuations can be captured using shorter horizons, this approach requires caution due to the potential influence of noise and seasonal effects. Although some experts suggest that several consecutive months are needed to confirm a market shift, others propose that a timeframe as short as a few weeks may be sufficient. An executive at a forecasting organization notes that while a single week's data cannot indicate a trend, observing changes over three or four weeks can reveal an inflection point, signaling that a market shift is underway. Some interviewed industry experts consider contract rates, but these are not typically used as a standalone metric. Leaders from two logistics firms emphasized that contract rates should be analyzed in conjunction with spot rates, as the former are significantly shaped by trends in the latter and can, to some extent, be forecasted based on spot rate movements. The truckload market often uses the spot rate as a leading indicator for where the contract rate is likely to go.

Tender-related KPIs are another metric used to assess overall market conditions in the truckload sector. Tendering is the process by which a shipper or broker requests a carrier to haul freight. In the context of the truckload market cycle, two primary metrics are widely used: 1) tender rejection rates, which measure the percentage of loads rejected by contracted, or primary, carriers (SONAR Knowledge Center, 2024), and 2) routing guide depth (RGD), which quantifies the number of tenders beyond the primary carriers that a shipper on average must contact before a load is accepted (Caza & Shekhar, 2022). Many interviewed practitioners indicate since truckload contracts do not guarantee freight volume, carriers have the discretion to reject loads, leading to instances where the primary carrier declines a shipment. As a result, shippers must reach out to additional carriers, increasing the number of transactions or RGD and raising tender rejection rates. Higher values for both metrics, often driven by better opportunities in the spot market, force shippers to seek extra capacity and increase spot and contract rates. According to an analyst at a major information company, higher RGD and tender rejection rates indicate a tight market, whereas lower values suggest a loose market.

Another key dimension of market analysis is freight demand and supply capacity. First, demand can be broken into two distinct categories: 1) freight volume, and 2) the broader economy and industries highly correlated with freight. Freight volume reflects the level of activity occurring in the market and represents the overall movement of goods across the country. Metrics within this category include the American Trucking Association's (ATA) Truck Tonnage Index, DAT's Load-to-Truck Ratio (LTR), the Bureau of Transportation Statistics (BTS) Ton-Mile Index, Cass Information System's Freight Index, and the Trucking Ton-Mile Index (Miller, 2024). As the U.S. economy expands, increased production and consumption drive higher demand in the FTL market. Economic indicators such as Gross Domestic Product (GDP), Personal Consumption Expenditure (PCE), and employment rates serve as key measures of economic activity and provide insights into freight demand. Additionally, during personal interviews, some experts suggested that manufacturing, commodity, housing, and retail industries are closely tied to the freight market and indicators representing these industries can offer valuable insights into freight demand. Second, on the supply side, experts use several metrics to measure freight capacity including the Federal Motor Carrier Safety Administration's (FMCSA) Carrier Authority, Class 8 Orders and Active Truck Utilization, and the ATA's employment data. Two interviewed experts also emphasize that tracking deadhead and empty miles, key indicators of operational efficiency, can provide valuable insights into market conditions such as capacity utilization.

Lastly, financial performance, particularly operating revenue and profit, is another lens through which experts assess the health of the truckload market. Eleven interviewed industry specialists assess the operating revenue and profit of FTL dry van companies as key indicators of the truckload market's state. One expert says it is common to evaluate the operating profits and revenues of large trucking companies (e.g. JB Hunt, Knight-Swift, and Heartland Express), brokers (e.g. Landstar and C.H. Robinson), and small carriers. FreightWaves, a data source for truckload industry analysis, leverages macro-carrier Knight-Swift's YoY revenue growth and quarterly earnings as key indicators for projecting the future trajectory of the truckload market cycle and broader industry trends (Hampstead, 2025).

In summary, spot and contract rates, tender rejection metrics, supply and demand indicators, and financial performance together provide a comprehensive view of the truckload market cycle. These measures help assess both the current state of the market and its future direction. When all four types of indicators increase, including rising spot rates, higher tender rejections, tighter capacity utilization, and improved financial performance, the market is considered tight. When these indicators decline, the market is considered loose, with lower demand, excess capacity, and weaker financial results. While spot rates and tendering metrics are leading indicators of the cycle, meaning they react in real time to shocks and are considered the first metrics to change as the cycle shifts, contract rates and financial performance are lagging indicators, meaning that they take a longer time to react to changing market conditions. Each indicator group contributes a different type of insight into the market cycle. Spot rates and tender rejection metrics capture real-time shifts in market behavior, offering early signals of change. Supply and demand indicators help explain the underlying forces driving the market, such as changes in freight volume, trucking capacity, or broader economic activity. These indicators provide a deeper understanding of why the market is tightening or loosening, rather than just showing that it is. Meanwhile, contract rates and financial performance metrics reflect longer-term trends.

2.2 Current Challenges

This section examines the current challenges the truckload industry faces in understanding and calculating the market cycle including inconsistent metrics, inadequate forecasting approaches, and benchmark methods.

After interviewing twenty industry experts, a picture emerged of the current practices used to track and predict future truckload market cycles. However, experts referenced many different metrics, and a more in-depth description of these indicators can be found in Section 3.3.1. While these metrics are useful for assessing market conditions, each provides a different perspective. As a result, there is currently no consensus-based metric to define the truckload market.

Without proper truckload business cycle forecasting practices in place, individual trucking companies and the industry as a whole face significant risks. Unforeseen changes throughout the cycle can affect factors the industry relies upon including fuel prices, consumer demand, and freight costs (Morgan, 2024). Reinforcing this concept, a data scientist at a logistics company highlights the impact of the COVID-19 pandemic, recalling the near-overnight drop in consumer demand during the first weeks of the shutdown and widespread uncertainty. This economic halt was quickly followed by a massive surge in demand after stimulus checks were issued, fueling at-home spending at a time when service-based industries were limited. Although the surge was promising while it lasted, the truckload business cycle has now experienced a prolonged downturn lasting three years. According to our interviews, this extended recessionary period has persisted longer than past cycles due to a sustained imbalance between excess capacity and weaker freight demand. While the pandemic itself could not have been predicted by even the most advanced technology, its effects can be analyzed to better understand the key drivers that most significantly impact the truckload market cycle.

Beyond the absence of a standardized set of metrics to track the truckload business cycle, the methods used to measure these indicators vary widely across the industry. Some experts rely on YoY comparisons, while others use index-based approaches that measure changes relative to a fixed baseline. For example, metrics such as the Trucking Ton-Mile Index, Cass Linehaul Index, and Bloomberg Commodity Index are calculated relative to a fixed benchmark, rather than compared to absolute values or changes over time. In addition to index-based methods, many experts in the industry use YoY metrics, comparing current values to those from the same time in previous years. For instance, an executive at a leading freight marketplace evaluates spot rates based on historical YoY comparisons rather than against a baseline index. While YoY values help remove noise from seasonality by first order differencing, they only show the percentage change from the same point twelve months earlier while the actual underlying value or magnitude of that change remains unknown. Some practitioners rely on raw, non-transformed values to observe trends over time. While these values reflect the current state of a metric, viewing them at a single point in time lacks the historical context needed to assess performance relative to the past.

Although each measurement approach may reflect similar trends and all raw data can be transformed into a benchmarked index or YoY metric, the use of different comparison methods makes it challenging to standardize interpretation and draw consistent conclusions across the industry.

3 Methodology

This research establishes a consensus-driven definition of the truckload market cycle and identifies indicators that can help predict future phase shifts. Chapter 3 describes the research methodology by exploring the data collection process (Section 3.1), cycle definition (Section 3.2), model selection process (Section 3.3), and Vector Autoregression (VAR) model (Section 3.4). The study identifies metrics that capture the state of the FTL industry's cycle by gathering insights from interviews with industry experts, a widespread survey, and existing research. Two dependent and multiple independent variables were selected for forecasting using time series modeling.

3.1 Data Exploration

Section 3.1 covers our data exploration, including insights from expert interviews and the industry survey (Section 3.1.1), as well as variable correlation analysis (Section 3.1.2).

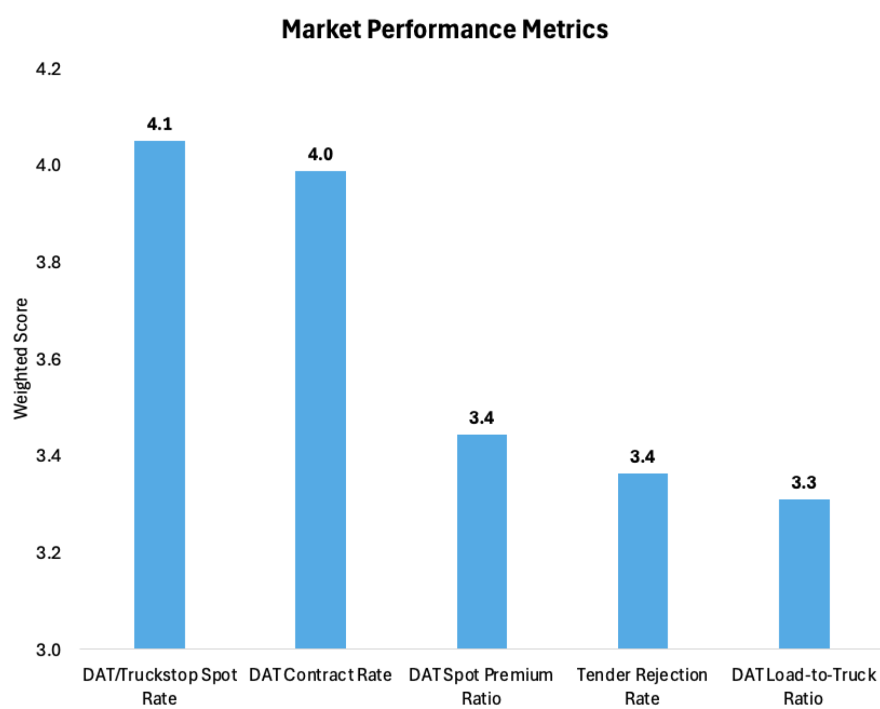
3.1.1 Deriving Variables from Interviews and Survey

Data can generally be interpreted in three primary forms: raw values, growth rate indictors such as month-over-month (MoM) or YoY, and indexed values, which normalize data against a fixed benchmark to enable easier comparison across time or categories. As part of the initial data exploration, we evaluated pros and cons of using raw data or transforming all data points to YoY metrics. While YoY data highlights changes in performance compared to the previous year, the calculation process results in the loss of one year of data at the start of each dataset. Additionally, information about the current state of the market condition is lost with YoY data as it compares with the previous year. Therefore, we chose raw data as an input for our forecast modeling.

After interviewing a diverse group of industry experts to gain insights into their perspectives on the truckload business cycle, a widespread survey was conducted to build upon expert opinions. The metrics included in the survey were derived from insights gathered during our expert interviews. We incorporated those findings into our broader survey to validate their relevance across a wider audience. The survey was distributed via email garnering 62 responses from 1,418 requests, LinkedIn with 49 responses, and C.H. Robinson's contacts resulting in 8 responses for a total of 119 survey participants. The survey posed seven questions which can be found in Appendix A.

Figure 5 shows the industry metrics most commonly used by survey respondents. The choices of metrics were determined based on frequently referenced indicators during expert interviews. In the survey, participants selected and rated metrics for evaluating market performance using a Likert scale from one to five, where one represented "Do not use" and five indicated "Highly useful." To calculate the average weighted score for a metric, each rating was multiplied by the number of respondents who selected it, the resulting products were summed, and the total was divided by the number of respondents. This score indicates how useful each metric is, with higher scores reflecting greater usefulness. Figure 5 highlights the top five metrics used, showing that respondents value DAT/Truckstop Spot Rates (US dollars per mile) the highest, with an average weighted score of 4.05 out of 5. Other top metrics include DAT Contract Rates (US dollars per mile), DAT Spot Premium Ratio, Tender Rejection Rate, and DAT Load-to-Truck Ratio. Although cited as the most frequently used metrics, practitioners use multiple methods of analyzing these metrics including raw, YoY, and indexed values. Therefore, this survey question sought to answer what variables are most common, but not the way the data is represented.

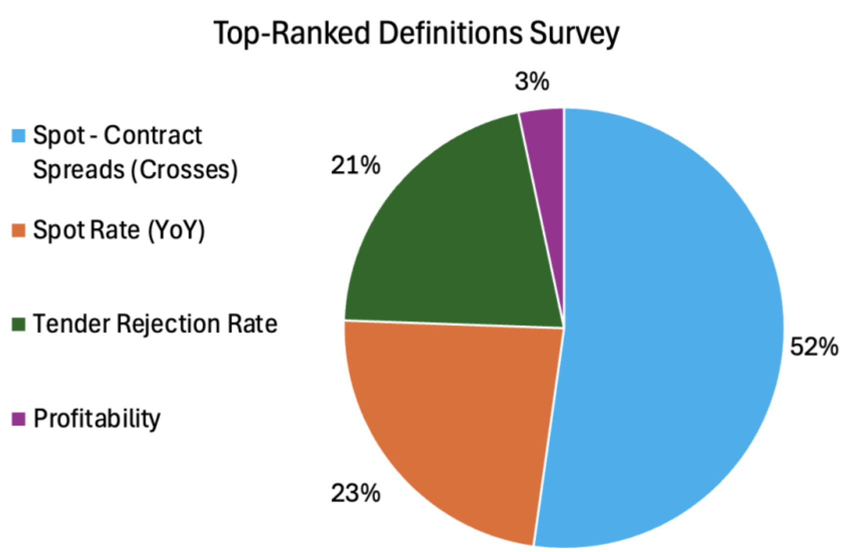
Figure 5: Market Performance Metrics



The second insight, shown in Figure 6, is derived from the definitions that were synthesized based on expert interviews. Respondents were asked to rank their preferred sets of definitions of tight (expansionary) and loose (contractionary) markets.

The majority of respondents (52%) found the definition "The TL market cycle is defined as a tight (expansionary) market when the spot rate crosses and exceeds the contract rate while it is defined as a loose (contractionary) market when the spot rate crosses and is below the contract rate" to be the most useful for making their business decisions. An additional 23% selected the definition "The TL market cycle is defined as a tight (expansionary) market when YoY percent changes in spot rate is positive for ≥ 3 consecutive months, while it is defined as a loose (contractionary) market when YoY percent change in spot rate is negative for ≥ 3 consecutive months." Meanwhile, 21% favored the definition "The TL market cycle is defined as a tight (expansionary) market when the tender rejection rate is increasing for ≥ 3 consecutive months, while it is defined as a loose (contractionary) market when the tender rejection rate is decreasing for ≥ 3 consecutive months." Finally, 3% indicated that "The TL market cycle is defined as a tight (expansionary) market when the revenue/profitability of publicly traded carrier companies (e.g., J.B. Hunt, Heartland Express, Knight-Swift) or independent smaller carriers is increasing for a sustained period, while it is defined as a loose (contractionary) market when the revenue/profitability of publicly traded carrier companies or independent smaller carriers is decreasing for a sustained period" is the most useful.

Figure 6: Top-Ranked Definitions Survey



Following the survey, we developed a set of indicators grounded in interviews and surveys to advance to our forecast modeling.

Table 1 presents the full list of independent variables used in our quantitative analysis to evaluate and forecast the truckload market cycle. Each variable was selected based on relevance to freight demand, capacity, economic activity, or pricing dynamics, as identified through both expert interviews and literature. The table provides a brief definition of each metric, along with its corresponding data source, which includes government databases, industry indexes, and private data providers. Together, these variables form the foundation of our model inputs and statistical evaluations.

Table 1: Independent Variables, Definitions, and Data Sources

Independent Variable	**Definition**	**Data Source**
Advanced Retail Sales	Monthly sales estimate of retail and food companies in the US (Federal Reserve Bank of St. Louis, n.d.)	Federal Reserve Bank of St. Louis
Bloomberg Commodity Index	Index derived of 24 commodities using futures contracts, weighted based on economic importance (Bloomberg Commodity index (BCOM), n.d.)	Bloomberg L.P.
Carrier Authority - Active	Total number of for-hire carriers (Federal Motor Carrier Safety Authority, 2024)	Federal Motor Carrier Safety Administration
Carrier Authority - Granted	Number of carriers granted permission by FMCSA to operate for-hire (Federal	Federal Motor Carrier Safety Administration

	Motor Carrier Safety Authority, 2024)	
Carrier Authority - Net	Difference between number of granted for-hire carriers and revoked for-hire carriers (Federal Motor Carrier Safety Authority, 2024)	Federal Motor Carrier Safety Administration
Carrier Authority - Reinstated	Number of carriers re-granted permission after revocation by FMCSA to operate for-hire (Federal Motor Carrier Safety Authority, 2024)	Federal Motor Carrier Safety Administration
Carrier Authority - Revoked	Number of carriers' permission suspended by FMCSA to operate for-hire (Federal Motor Carrier Safety Authority, 2024)	Federal Motor Carrier Safety Administration
Class 8 Backlogs*	Quantity of Class 8 trucks that are on order but not manufactured (ACT Research, n.d.)	ACT Research
Class 8 Build*	Quantity of Class 8 trucks manufactured for use in the US (ACT Research, n.d.)	ACT Research
Class 8 Cancel*	Quantity of Class 8 truck orders that are canceled (ACT Research, n.d.)	ACT Research

Class 8 Gross*	Quantity of monthly Class 8 truck order quantity (ACT Research, n.d.)	ACT Research
Class 8 Inventory*	Quantity of Class 8 trucks that have been manufactured and awaiting shipment to customer (ACT Research, n.d.)	ACT Research
Class 8 Net*	Difference of Class 8 Gross minus Class 8 Cancel (ACT Research, n.d.)	ACT Research
Class 8 Retail Sales*	Quantity of Class 8 truck orders to final customers (ACT Research, n.d.)	ACT Research
CRB Commodity Index	Average of futures prices for 19 raw materials, adjusted monthly. These commodities are categorized by energy, agriculture, precious metals, and base/industrial metals (*CRB commodity index*, n.d.)	Thomson Reuters/CoreCommodity
Freight Transportation Services Index	Annual measurement of freight volume throughout the US (IBISWorld Industry Reports, n.d.)	Federal Reserve Economic Data

Housing Starts	Monthly number of new housing units that have begun construction in the US (Federal Reserve Bank of St. Louis, n.d.)	Federal Reserve Economic Data
Industrial Production Index	Total output of all industrial facilities located in the US (Federal Reserve Bank of St. Louis, n.d.)	Federal Reserve Economic Data
Load-Truck Ratio*	Total number of freight loads listed on DAT's load board divided by the number of available trucks for hauling (Dorf, 2016)	DAT
M1 Money Supply	Measure of liquid US money supply that can be spent immediately (Federal Reserve Bank of St. Louis, n.d.)	Federal Reserve Economic Data
M2 Money Supply	M1 Money Supply plus near money (savings, deposits) (Federal Reserve Bank of St. Louis, n.d.)	Federal Reserve Economic Data
Manufacturing New Orders Index	Month-over-month manufacturing order quantities (Majestic Steel USA, n.d.)	Institute for Supply Management
Manufacturing Purchasing Index	Monthly measurement of US manufacturing production (Kopp, 2024)	Institute for Supply Management

Merchant Wholesalers: Inventories to Sales Ratio	Ratio of end-of-month inventory values to monthly sales (Federal Reserve Bank of St. Louis, n.d.)	Federal Reserve Economic Data
Producer Price Index	The average change over time in the selling prices received by domestic producers for their output (U.S. Bureau of Labor Statistics, n.d.)	Bureau of Labor Statistics
Routing Guide Depth	The number of tenders made before tender acceptance (Caza & Shekhar, 2023)	C.H. Robinson
S&P Commodity Index	Commodity market benchmark (Hayes, 2022)	Goldman Sachs
Truck Tonnage Index	Monthly measurement of the gross weight of freight transported by motor carriers in the US (Federal Reserve Bank of St. Louis, n.d.)	Federal Reserve Economic Data
U.S. No 2 Diesel Retail Prices	Average cost per gallon of diesel fuel (U.S. Energy Information Administration (EIA, n.d.)	U.S. Energy Information Administration
Vehicle Sales	Predicted annual vehicle sales based on monthly	Federal Reserve Economic Data

	sales data (Federal Reserve Bank of St. Louis, n.d.)	
Trucking Ton-Mile Index (TTMI)*	Measures demand for for-hire trucking services by calculating weighted ton-miles moved across key industry sectors at the national level (Croke, 2023)	(Miller, 2024) (Miller & Bolumole, 2022)

* Not publicly available

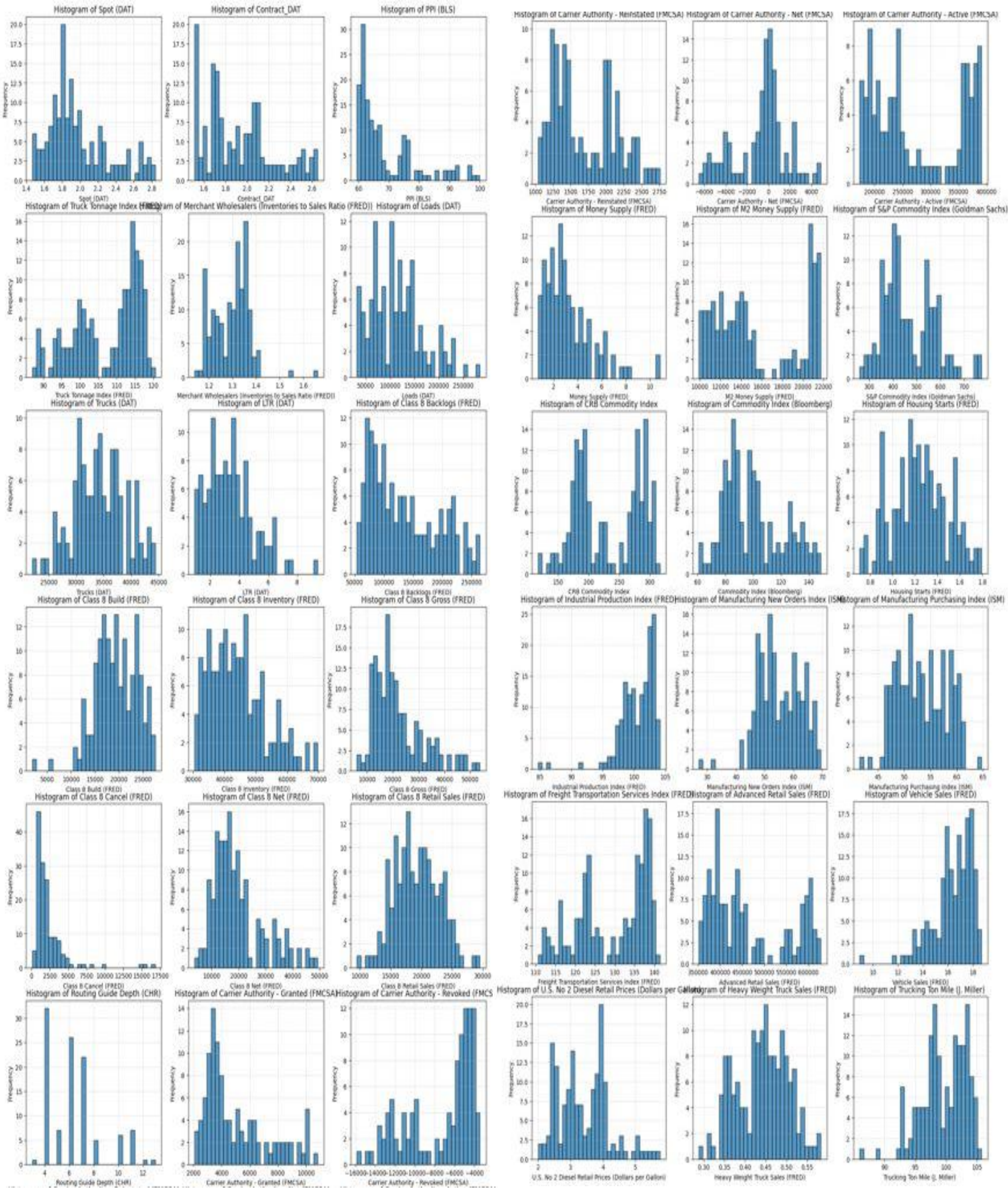
Table 2 provides summary statistics using monthly data from April 2012 to March 2025, subject to data availability for each independent variable. The summary statistics help determine if all variables have the same amount of available data (count), the mean (average), standard deviation, minimum, 25th percentile, 50th percentile, 75th percentile, and maximum. These statistics determine if the variable displays a normal, left, or right skewed distribution that later determines how the variable is scaled for modeling. The summary statistics provide foundational insight into the distribution and completeness of each independent variable used in our model. These metrics are critical for understanding the shape and behavior of the data prior to modeling. The mean and median help evaluate the symmetry of the data. When these values differ, it may indicate a skewed distribution. Similarly, large differences between the 25th and 75th percentiles suggest high variability or potential outliers. This information guides our decisions on scaling methods, helping determine whether a variable should be treated with a linear or logarithmic transformation.

Table 2: Summary Statistics for Forecasting

Metric	Count	Mean	Std Dev	Min	25%	50%	75%	Max
Advanced Retail Sales (FRED)	152	464,703	87,699	352,053	393,464	436,688	554,697	627,915
Carrier Authority - Active (FMCSA)	108	276,072	76,593	173,416	206,524	245,442	361,484	397,070
Carrier Authority - Granted (FMCSA)	108	5,021	2,273	2,086	3,315	4,061	6,271	10,365
Carrier Authority - Net (FMCSA)	108	-2,620	2,260	-7,534	-3,082	-2,240	528	2,876
Carrier Authority - Reinstated (FMCSA)	108	1,690	442	1,039	1,308	1,544	2,053	2,876
Carrier Authority - Revoked (FMCSA)	108	-7,390	4,004	-15,873	-10,375	-5,800	-4,561	-3,444
Class 8 Backlogs (ACT)	149	133,756	57,973	26,417	88,815	126,475	176,305	264,575
Class 8 Build (ACT)	149	19,390	1,830	16,492	19,496	20,237	27,575	27,575
Class 8 Cancel (ACT)	149	2,292	1,493	0	1,062	1,682	2,864	8,831
Class 8 Gross (ACT)	149	21,953	9,887	6,072	16,469	19,277	25,626	53,721
Class 8 Inventory (ACT)	149	44,250	8,895	30,472	37,277	43,002	49,716	69,757
Class 8 Net (ACT)	149	19,661	9,439	3,678	12,981	16,943	23,189	49,208
Class 8 Retail Sales (ACT)	149	19,203	3,099	9,510	16,629	19,435	21,789	26,831
Commodity Index (Bloomberg)	152	93.08	31.12	48.04	96.57	114.25	148.51	148.51
Contract (DAT)	153	1.92	0.34	1.51	1.71	1.88	2.11	2.65
CRB Commodity Index	154	230.98	53.31	117.84	221.18	221.18	254.25	316.57
Freight Transportation Services Index (FRED)	151	129.42	8.78	110.6	122.35	132.6	137.4	141.4
Heavy Weight Truck Sales (FRED)	149	9.63	3.66	85.99	97.64	100.21	102.59	105.6
Housing Starts (FRED)	152	1.24	0.25	0.71	1.08	1.23	1.42	1.94
Industrial Production Index (FRED)	152	103.07	8.27	86.8	97.68	101.67	109.1	120.6
Load-to-Truck Ratio (DAT)	116	3.38	1.61	0.92	2.15	3.16	4.76	8.03
M2 Money Supply (FRED)	152	15,559	1,099	11,899	15,282	15,426	17,082	21,723
Manufacturing New Orders Index (ISM)	153	55.09	7.49	27.1	49.8	54.5	61.1	69.47
Manufacturing Purchasing Index (ISM)	153	54.09	7.49	27.1	49.8	54.5	61.1	69.47
Merchant Wholesalers (Inventories to Sales Ratio) (FRED)	150	1.3	0.08	1.14	1.24	1.28	1.34	1.48
Money Supply (FRED)	152	3.22	1.99	0.98	1.27	1.44	4.14	7.11
Producer Price Index (BLS)	151	68.74	9.98	59.39	61.78	64.25	74.68	84.68
Routing Guide Depth (CHR)	116	6.28	2.03	3.15	4.06	6.21	8.71	10.1
S&P Commodity Index (Goldman Sachs)	152	467.18	109.65	258.87	387.23	435.79	545.26	773.67
Spot (DAT)	153	1.98	0.34	1.47	1.71	1.89	2.18	2.84
Truck Tonnage Index (FRED)	149	109.91	6.89	97.2	104.5	109.2	115.1	120.5
Trucking Ton Mile (J. Miller)	149	99.63	3.66	85.99	97.64	100.21	102.59	105.6
U.S. No 2 Diesel Retail Prices (Dollars per Gallon)	154	3.41	0.79	2	2.79	3.32	4.12	5.81
Vehicle Sales (FRED)	152	15.41	3.79	8.2	12.3	14.8	18.1	22.2

Additionally, Figure 7 presents the skewness of each variable, which informs the selection of appropriate scaling methods discussed in Section 3.4.1. The distribution of the raw data determines whether a logarithmic transformation (for right-skewed distributions) or a linear transformation (for left-skewed or normal distributions) should be applied.

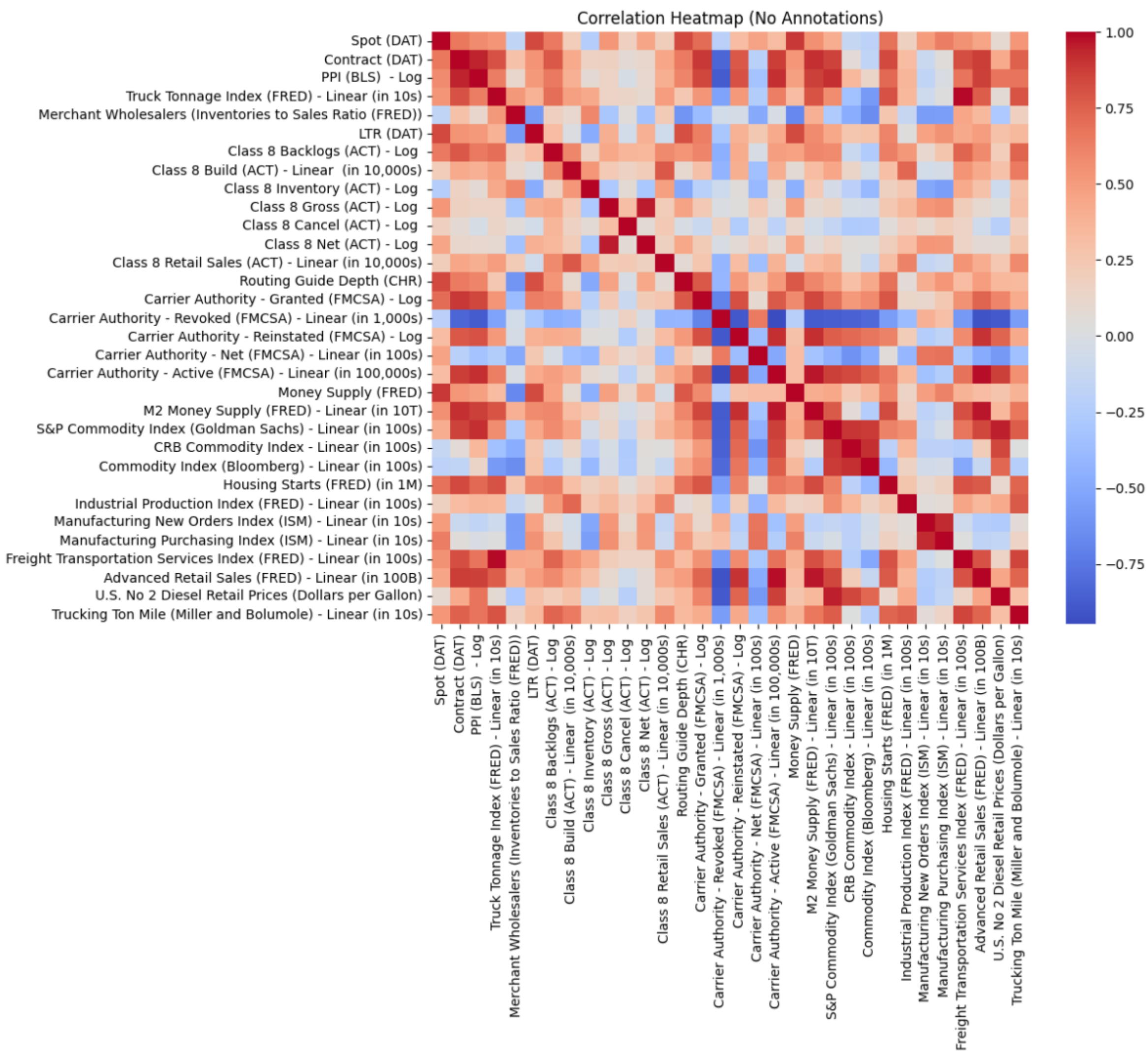
Figure 7: Distributions of Independent Variables



3.1.2 Variable Correlation

After collecting the data, we constructed a correlation matrix using same-month data, without accounting for lag effects, to identify initial patterns and highlight variables with strong contemporaneous relationships, as shown in Figure 8. By examining same-month correlations, we gained early insights into which indicators may be most interconnected and potentially influential in the truckload market cycle.

Figure 8: Correlation Heat Map



Based on our interview and survey findings, spot and contract rates emerged as the most prevalent metrics in the industry. Consequently, we focused our analysis on the correlation between spot and contract rates and all independent variables in this section.

Shown in Table 3, Money Supply, LTR, and RGD are highly correlated with spot rate (correlation $\geq$ 0.8 or ≤ -0.8). On the other hand, Table 4 shows contract rate is highly correlated (correlation $\geq$ 0.8 or ≤ -0.8) with PPI, Money Supply (M2), Advanced Retail Sales, Carrier Authority – Active, Carrier Authority – Granted, S&P Commodity Index, Housing Starts, Carrier Authority – Revoked, Freight Transportation Services Index, and Truck Tonnage Index.

Table 3: Strongest Same-Month Correlations Between Independent Variables and Spot (DAT)

Variable	**Spot (DAT)**
Money Supply (FRED)	0.89
Load-to-Truck Ratio (DAT)	0.84
Routing Guide Depth (CHR)	0.84

Table 4: Strongest Same-Month Correlations Between Independent Variables and Contract (DAT)

Variable	**Contract (DAT)**
Log(PPI (BLS))	0.94
M2 Money Supply (FRED)	0.91
Advanced Retail Sales (FRED)	0.87
Carrier Authority – Active (FMCSA)	0.87
Log(Carrier Authority – Granted (FMCSA))	0.87
S&P Commodity Index (Goldman Sachs)	0.86
Housing Starts (FRED)	0.84
Carrier Authority - Revoked (FMCSA)	(0.83)
Freight Transportation Services Index (FRED)	0.82
Truck Tonnage Index (FRED)	0.82

Correlation analysis allows us to assess how variables are related to each other at a specific point in time. While this provides a useful initial snapshot, it has important limitations. The correlation matrix does not capture how relationships evolve over time or whether one variable influences another (causality). At this stage, our goal is to identify correlations between potential explanatory variables and spot/contract rates. However, temporal dynamics are addressed later in Section 3.4 regarding the Vector Autoregression (VAR) model which incorporates lagged values to capture timing effects across variables.

3.2 Cycle Definition

Given the insights from our expert interviews, survey, and in partnership with C.H. Robinson, we developed a four-phase cycle definition of the truckload market cycle, different than those developed by ACT Research and RXO, outlined in the Introduction chapter. These metrics were chosen to represent the truckload market cycle since the majority of truckload professions cited them as preferred and useful metrics. The four phases are: *Expansion*, *Peak Transition*, *Contraction*, and *Trough Recovery*, as detailed in the following paragraphs.

Expansion begins when both the YoY spot rate and the spot premium ratio cross above zero on the horizontal axis, shifting from negative to positive. This crossover marks the start of a new cycle. While the order in which the spot rate or spot premium ratio crosses above zero is negligible, it is essential that both surpass zero to confirm the start of the cycle. This requirement helps ensure that minor fluctuations in either metric do not falsely indicate the beginning of a new cycle. During *Expansion*, the YoY change in both the spot rate and the spot premium ratio exceed their values from the previous year. *Expansion* continues until the *Peak Transition* occurs. *Expansion* is characterized by increasing freight demand and/or a reduction in carrier supply.

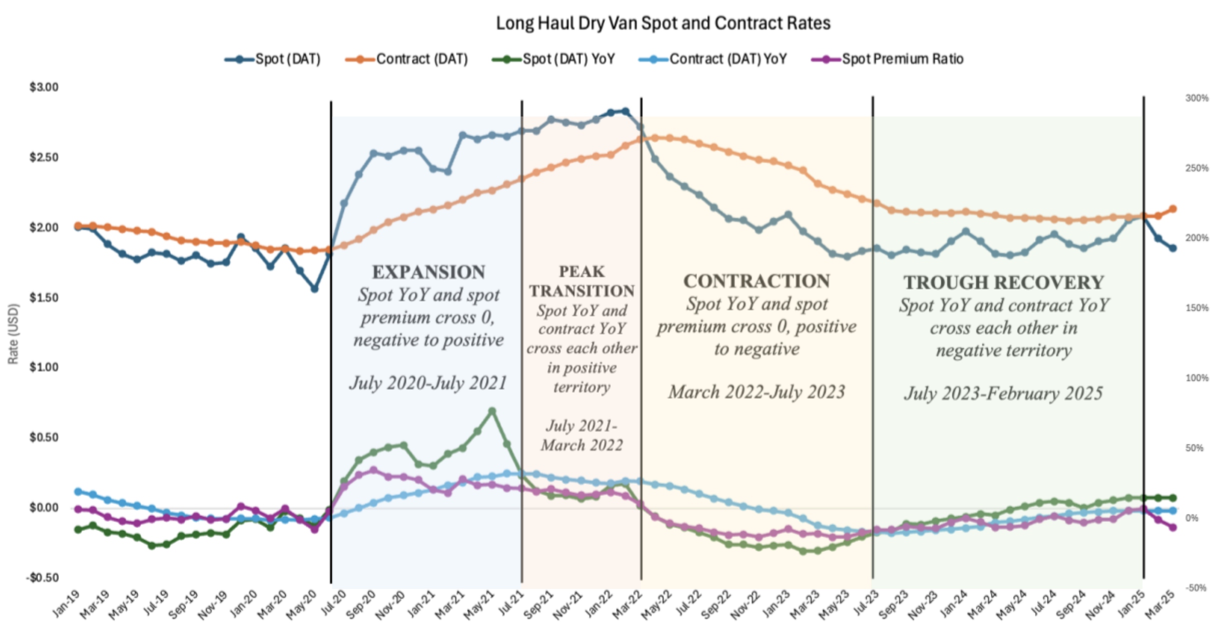
Peak Transition commences when the YoY spot and contract rates intersect, with both being positive. At this point, the two YoY rates reach equilibrium. Both rates remain in positive territory and spot and contract YoY rates continue to exceed their values from the previous year. *Peak Transition* is typically characterized by a moderate reduction in freight demand and/or an increase in carrier supply.

Contraction begins when both the YoY spot rate and the spot premium ratio cross below zero on the horizontal axis, shifting from positive to negative. As in *Expansion*, the order in which the spot rate or spot premium ratio crosses first is negligible; however, it is essential that both have moved below zero to confirm the start of *Contraction*. At this point, the YoY change in both the spot rate and the spot premium ratio falls below their values from the previous year. *Contraction* is typically characterized by a decrease in freight demand and/or an increase in carrier supply.

Trough recovery is triggered when the YoY spot and contract rates intersect and both are negative. The YoY rates reach equilibrium and remain in negative territory indicating they continue to be below their values from the previous year. *Trough Recovery* is characterized by a period of moderate increase in rates, though conditions remain challenging, with a slight rise in freight demand and/or a reduction in carrier supply.

As the cycle is defined, we have identified target variables: spot rate (YoY), contract rate (YoY), and the spot premium ratio. The YoY rates and spot premium ratio will be derived later through simple arithmetic. Figure 9 depicts the anatomy of the business cycle using this definition using spot and contract rates from DAT.

Figure 9: Cycle Definition on COVID-19 Pandemic Cycle



3.3 Model Selection

We looked at three methods of modeling the truckload market cycle: Ordinary Least Squares (OLS) regression, Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX), and Vector Autoregression (VAR).

3.3.1 Model Type Considerations

After conducting an initial exploration of the data, we ran an OLS regression model with the objective of forecasting spot and contract rates for 24 months in the future. To assess the feasibility of OLS, we initially evaluated the impact of each independent variable and its lagged values (up to six months) on spot rate only. The analysis revealed that only variables from the past two months were statistically significant to spot rate, using a p-value threshold of ≤ 0.1. While this suggested that OLS could capture short-term relationships, it quickly became evident that the model lacked the predictive strength needed for long-term horizons. Ultimately, OLS proved valuable as an exploratory tool but was not suitable for long-term forecasting.

Next, we considered an Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model to forecast spot and contract rates. However, ARIMAX assumes a one-directional relationship, where only independent variables influence a single dependent variable, without interconnectedness between them. In reality, spot and contract rates are interdependent. During expansion, a high contract rate often pushes spot rates even higher, and persistently high spot rates can lead shippers and carriers to agree on higher contract rates. Because ARIMAX cannot simultaneously model this mutual dependence using multiple independent variables, it is not suitable for our forecast.

The Vector Autoregression (VAR) model effectively captures relationships among multiple time series variables by treating each as a dependent variable while also incorporating lagged values. This approach was particularly valuable for our research as it allows us to analyze the bi-directional relationship between spot and contract rates as well as the effect of each variable's lagged terms. Section 3.4 explains the intricacies of the chosen model, VAR.

3.4 Vector Autoregression (VAR) Model

The Vector Autoregression Model (VAR) is a linear statistical model for multivariate time series that incorporates past lags of both the dependent variables (spot and contract rates) and independent variables (features). The model captures the interrelationships among all variables using multiple historical values, or lags, to forecast future values. The VAR model combines weighted external influences, historical patterns, and a random error term to produce forecasts. We selected this approach to jointly predict two interdependent variables while accounting for a range of external factors that also impact them. VAR(p) is given by

$$\boldsymbol{y_t} = \boldsymbol{c} + \boldsymbol{\Phi_1 y_{t-1}} + \boldsymbol{\Phi_2 y_{t-2}} + \ldots + \boldsymbol{\Phi_p y_{t-p}} + \boldsymbol{w_t}$$

where:

$\boldsymbol{y_t}$ is a column vector of the variables at time t

$\boldsymbol{c}$ is a column vector of intercepts

$\boldsymbol{\Phi_j}$ is a matrix of coefficients when capturing relationship of variables in $\mathbf{y_t}$

$\boldsymbol{y_{t-j}}$ is a column vector of variables at time t − j

$\boldsymbol{w_t}$ is an error term or white noise column vector at time t where $\mathrm{cov}(\mathrm{w_t}, \mathrm{w_s}) = 0$, $\mathrm{s} \neq \mathrm{t}$

p is an optimal lag chosen by the model using AIC function (discussed later in section 3.4.5)

To clarify how our variables are structured within the VAR(p) framework, we expand the equation above into matrix form below.

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \phi_{11}^1 & \phi_{12}^1 \\ \phi_{21}^1 & \phi_{22}^1 \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} \phi_{11}^2 & \phi_{12}^2 \\ \phi_{21}^2 & \phi_{22}^2 \end{bmatrix} \begin{bmatrix} x_{t-2} \\ y_{t-2} \end{bmatrix} + \cdots$$
$$\begin{bmatrix} \phi_{11}^p & \phi_{12}^p \\ \phi_{21}^p & \phi_{22}^p \end{bmatrix} \begin{bmatrix} x_{t-p} \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} w_{t,1} \\ w_{t,2} \end{bmatrix}$$

In our baseline model, the vector $\boldsymbol{y_t}$ includes two variables, x_t and y_t ,which represent spot and contract rates.

Next, we interpret the coefficient matrix ($\boldsymbol{\Phi}_j$) to analyze the dynamic relationships between the variables in the vector autoregression (VAR) model. Specifically:

- ϕ_{11}^1 represents the effect of x_{t-1} on x_t

- ϕ_{12}^1 represents the effect of y_{t-1} on x_t
- ϕ_{21}^1 represents the effect of x_{t-1} on y_t
- ϕ_{22}^1 represents the effect of y_{t-1} on y_t

This structure allows us to understand how lagged values of each variable influence the current values of both. The remaining lag terms (from lag 2 to lag *p*) follow the same interpretation pattern (Zivot, n.d. and Rajab et al., 2022).

One of the core assumptions of the VAR model is that all time series in $\boldsymbol{y_t}$ must be stationary. To meet this requirement, data transformation, or differencing, may be necessary for variables like spot rates, contract rates, and other independent variables. This preprocessing step is discussed further in Section 3.4.4.

Once stationarity is achieved, the model is estimated by selecting the optimal number of lags, using the Akaike Information Criterion (AIC), as described in Section 3.4.5. The VAR model applies a uniform optimal lag length (p) across all variables, which can be a limitation since, in reality, different variables may exert influence over varying time horizons. To address this limitation, we conduct a separate analysis of the most impactful lag for each variable, detailed in Section 4.2.

The estimation process produces coefficients for every variable at each lag, which are then used to generate forecasts. In addition to estimating coefficients, this step also includes the Granger Causality Test, which evaluates whether one variable (including its lagged values) statistically influences another. Further details on this are provided in Section 3.4.6. Finally, forecasts are then produced using the VAR(p) model.

3.4.1 Data Transformation

We apply a manual feature scaling method before inputting the data into our VAR model to enable comparability and ensure interpretability. This manually transformed data is used for both the Granger Causality Test (Section 3.4.6) and forecasting within the VAR model. For variables requiring scaling, we apply either a linear or logarithmic transformation based on the distribution of the data, presented in Figure 7. Variables exhibiting a left-skewed or approximately normal distribution are scaled using a linear transformation defined as $X' = \frac{X}{Scale(X)}$. As an example, \$1,100 is scaled to \$1.1 by dividing \$1,100 by 1,000. This method helps maintain the interpretability of coefficients and forecasts across variables with different scales, such as those measured in millions compared to others with single-digit values. For variables that are right-skewed, we apply a logarithmic transformation to reduce skewness and stabilize the variance, helping to prevent heteroscedasticity that would violate the VAR model assumptions (Ford, 2018).

3.4.2 Training and Testing Data

To train and test our model, we utilize spot and contract rates from the national long-haul dry van FTL market, obtained from DAT Freight & Analytics due to its data accessibility and completeness. The dataset has a monthly cadence and covers three truckload market cycles from April 2012 to March 2025. To analyze cycle dynamics, we trained the model using data from two complete cycles (April 2012 to June 2020) and evaluated forecast accuracy using one full cycle covering July 2020 to March 2025. However, since certain data sources begin after April 2012, some model iterations have varying training start dates. Importantly, we split the data before applying any transformations to prevent data leakage and ensure the test set remains fully independent from the training set.

3.4.3 Decomposition

Because the goal is to forecast cycle dynamics, we remove noise to eliminate false fluctuations and improve forecast accuracy. Hence, the first preprocessing step is to implement a seasonal decomposition technique to separate the trend, seasonality, and residual in order to analyze each component. Trend refers to the long-term direction of the dataset's mean. Seasonality refers to the data's patterns at fixed intervals and the tendency to rise and decline at specific points over time (e.g., the 15th of each month, holidays, etc.). Residual refers to the error term, or the irregular component of the time series. We used additive decomposition as both spot and contract rates exhibit constant seasonal variation over time.

As a time series, additive decomposition takes the following form:

$$Y_t = T_t + S_t + R_t$$

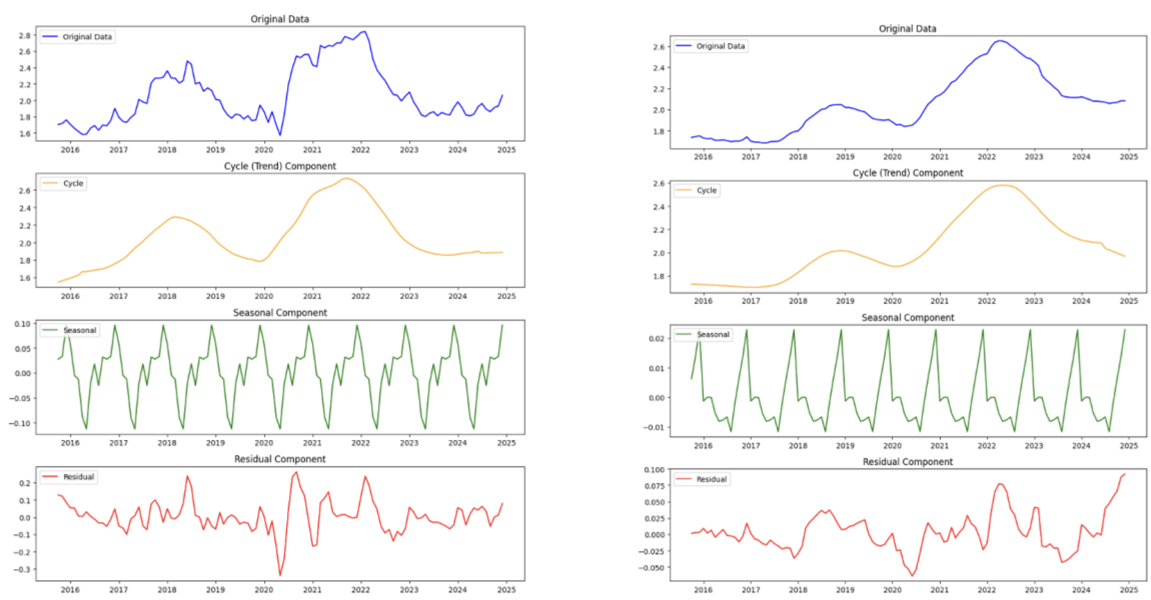
where:

- T = trend
- S = seasonality
- R = residual (Penn State Eberly College of Science, n.d.-a)

Figure 10 displays the seasonal decomposition of DAT's spot and contract rates. All graphs represent time in months on the horizonal axis. The decomposition chart consists of four components:

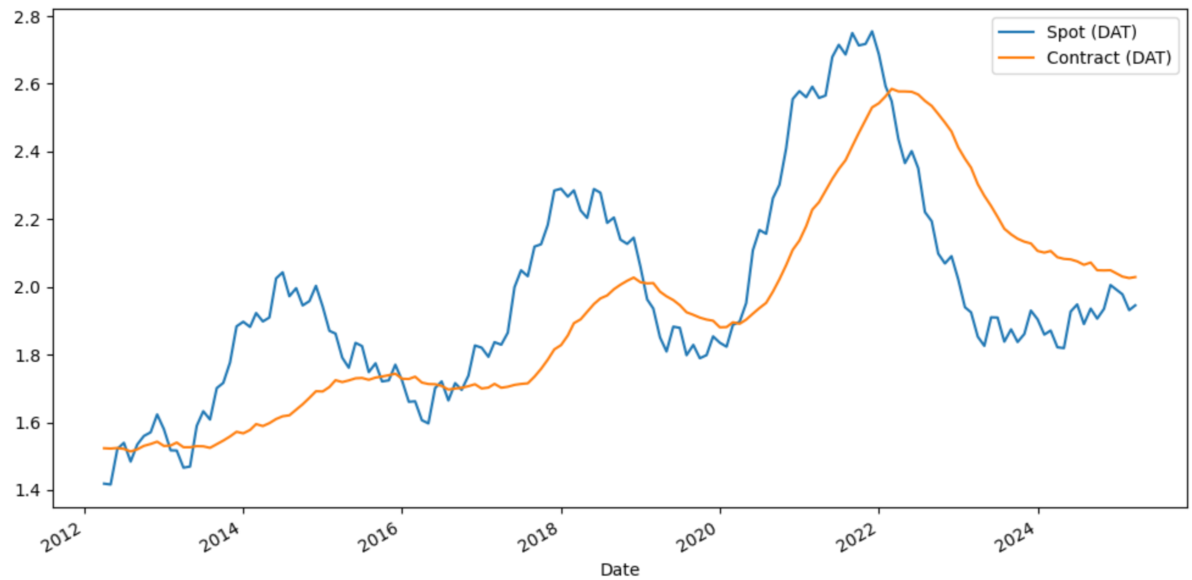
- Original Data – Represents the actual rates
- Trend (Cycle) – While called the trend component, the behavior closely resembles that of a cycle. For the purpose of this capstone, we use this component to represent the cyclical pattern in rates, focusing on its behavior rather than its technical label.
- Seasonality – Reflects regular rate fluctuations
- Residual – Represents the unpredictable component of the rates

Figure 10: Seasonal Decomposition



For our model, we removed only the residual component, retaining both the trend (which represents the cycle) and seasonality to ensure the forecast remains as close as possible to the original scale, as shown in Figure 11.

Figure 11: Spot and Contract Trend (Cycle) and Seasonality



As mentioned before, after decomposing the data we found that the seasonal_decompose function from statsmodels' time series analysis (tsa) (called 'trend') closely aligns with the cycle pattern, as the statsmodels package in Python does not separate these components but instead combines them into a single estimate (Penn State Eberly College of Science, n.d.-a). This package employs a Centered Moving Average approach to filter the time series and takes the form $T_t = \frac{X_{t-d+1}+\cdots+X_{t+d-1}+X_{t+d}}{p}, d = \frac{p-1}{2}, p\ is\ odd$ and $T_t = \frac{0.5X_{t-d}+X_{t-d+1}+\cdots+X_{t+d-1}+0.5X_{t+d}}{p}, d = \frac{p}{2}, p\ is\ even$

where:

- p = window size (i.e., the total number of observations used to compute the moving average centered at time *t*).
- d = half-window length, used to determine how far back and forward from time *t* the averaging window should extend (Statsmodels, 2023)

We set p = 12 to represent monthly data, allowing the model to capture annual seasonal patterns that recur every 12 months. For context, p would be set to one for annual data and four for quarterly data. The cycle component is referred to as the trend-cycle component (Huang & Petukhina, 1970). Therefore, for the remainder of this research, the trend and cycle component will be one and the same (labeled as 'Cycle (Trend)' in the figures).

3.4.4 Data Stationary

The VAR model assumes time series variables are stationary. Stationarity refers to the data maintaining a near-constant mean and variance throughout the time series. Therefore, to test whether the original data is stationary, we applied the Augmented Dickey-Fuller (ADF) test to all variables in the model using the adfuller function from Python's statsmodels time series analysis (tsa) tools (stattools module) library. The ADF test assumes a null hypothesis that the data is non-stationary. We chose to set the threshold of a p-value less than or equal to 0.05 to reject the null hypothesis. Therefore, if the ADF test yields $p - value \leq 0.05$, the data is stationary.

For any variables that have a p-value above 0.05, it is necessary to make them stationary through a differencing process in the following form.

$$Y_t' = Y_t - Y_{t-1} \in \{2,3,\dots,\mathrm{T}\} \text{ where T is the number of time periods.}$$

In the case that the data is not stationary after a single differencing, it is necessary to take a second-order difference to make the data stationary. This can be achieved with the following formula.

$$Y_t'' = Y_t' - Y_{t-1}' \in \{2,3,\dots,\mathrm{T}\} \text{ where T is the number of time periods.}$$ (Kwiatkowski et al., 1992)

Differencing continues until the data becomes stationary before inputting it into the VAR model.

3.4.5 Maximum Lag

We implement the Akaike Information Criterion (AIC) function to choose the optimal number of lags. The optimal lag is found by determining the most significant lagged value of any given variable by minimizing the AIC, a numerical value that measures the goodness of fit of a particular lag. The AIC is given by $AIC = 2K - 2\ln(L)$

where:

- K = number of independent variables
- L = log-likelihood estimate (Bevans, 2023)

Choosing appropriate lag lengths in the VAR model is critical as using a lagged value too low misses important trends and patterns in the training data, while too large of lags may overfit the model and introduce greater error to the forecast (Jimoh, 2023).

For each model, we balance the number of lags (p) with the number of variables (N). This is because the number of estimated parameters in a VAR model should be less than the number of observations, following the formula:

$$Total\ Number\ of\ Parameters = (N \times p + 1) \times N.$$

Exceeding this limit increases standard errors, leading to unreliable hypothesis testing, poor forecast performance, and model computation failure (Lütkepohl, 2005).

We found that the model selects optimal lags between 11 and 12 which aligns with our expectation, as longer lags effectively capture fuller cycle dynamics. Thus, we set the maximum lags between 11 or 12 in the VAR model. However, due to the number of observations ranging from 116 to 153, the model is limited to using fewer than six variables due to the reason stated above.

3.4.6 Variable Selection using Granger Causality Test

We applied the Granger Causality test on the training set to evaluate whether each independent variable had a significant impact on spot and contract rates. The test examines pairwise relationships within the model after VAR runs with optimal lags. The Granger Causality test evaluates two or more variables to determine their relationship based on the temporal components of time series data (Shojaie & Fox, 2022). This test is used to prove if independent variable X causes dependent variable Y or vice versa. The Granger Causality test is a hypothesis test with the null (H_0) indicating that a lagged value of X does not cause Y and the alternative (H_1) indicates that a lagged value of X does cause Y (Bobbitt, 2021).

The Granger Causality test uses both spot and contract rates as the dependent variables based on the majority consensus from both interviews and survey responses. The test provides each variable's statistical significance (p-value). We implemented a three-tier system of statistical significance based on standard practice, displayed in Table 5.

Table 5: P-Value Significance Thresholds for Granger Causality Test

P-Value	Interpretation
P-Value > 0.01	X does not significantly cause Y, or vice versa
0.05 < P-Value < 0.1	X significantly causes Y, or vice versa moderately
0.01 < P-Value < 0.05	X significantly causes Y, or vice versa
P-Value < 0.01	X significantly causes Y, or vice versa strongly

We refined the VAR model by including only variables that significantly Granger-cause both spot and contract rates, while also preserving the causal relationship between spot and contract rates themselves. With these selected variables, we analyzed their coefficients, forecast errors, and used them to build the final forecast.

3.4.7 Stability Condition Check

To ensure reliable forecasting, we assess the stability of the system in the VAR model. The Stability Condition Check verifies the stability of the system of equations after running the VAR, rather than evaluating individual variables independently. Mathematically, the stability condition confirms whether the system is stable by checking if all eigenvalues are less than one in absolute value. Eigenvalues indicate how the system evolves over time—whether it remains stable or becomes unstable (StataCorp LLC, n.d.; Katzman et al.). However, higher lags increase the risk of system instability. This trade-off is important to consider when forecasting long-term, as we sacrifice some stability of the system to capture the cycle dynamic.

3.4.8 Forecast and Model Validation

Evaluating a model's performance based on the training and test data is critical for assuming confidence in the out-of-sample forecast. Because we are not simply forecasting the dollar values for the spot and contract rates (dependent variables), but the date of the cycle shift, we employ two types of error metrics to validate the model. First, we use the standard error metric, Mean Absolute Percent Error (MAPE), to find the lowest error values. We then introduce our primary error metric, *timing error*, which measures how far off our forecast is from the actual phase shift. The shift is defined based on the cycle definitions in Section 3.2. This metric captures how accurately the model predicts the timing of transitions in the truckload market cycle given by

$$E^{(i)} = |T^{(i)}{}_{actual} - T^{(i)}{}_{forecast}|, \text{ where}$$

- $T^{(i)}{}_{actual}$ is the actual start time of phase i
- $T^{(i)}{}_{forecast}$ is the forecasted start time of phase i
- $E^{(i)}$ is the timing error i

To evaluate the metric's ability to capture bias, we assess how well it reflects both the accuracy and consistency of the phase shift's timing. First, our metric measures the magnitude of deviation (in months) between the forecasted and actual timing of each phase shift. We focus on the absolute value of these errors to avoid the misleading effect of averaging signed values—particularly important in long-term forecasts where average timing error is critical. For example, a -2 error (indicating the forecasted shift occurs two months later than the actual, or an overestimate) and a +2 error (indicating the forecasted shift occurs two months earlier, or an underestimate) would cancel each other out, falsely suggesting zero error and masking actual forecast error. Therefore, we choose to look at absolute values where a timing error of two means the forecasted phase shift deviates from the actual timing by two months, regardless of whether it is early or late. Second, in addition to average timing error, we also examine the standard deviation of timing errors across all four phases to assess the consistency of model performance. However, since our testing dataset includes only a single full cycle, we capture just one data point per phase, resulting in four data points per cycle. This may limit the robustness of our model's accuracy assessment and introduce overfitting. Nevertheless, given the specific objective of this capstone to forecast the timing of shifts within and between cycles, this metric remains the most practical and appropriate choice.

As described in Section 3.4.6, if the Granger Causality test reveals no statistical significance ($p\text{-value} \geq 0.1$) for any of the following relationships—spot causing contract, contract causing spot, independent variable causing spot, or independent variable causing contract—then that independent variable is excluded from further analysis. The remaining variables are then introduced into the model one at a time to assess their predictive power based on MAPE and timing error.

Next, for long-term forecasting, the dataset is split in July 2020, coinciding with the conclusion of the first two cycles, to allow testing on the third cycle and capture complete cycle dynamics. After introducing each variable, the model's forecast accuracy is re-evaluated. If the inclusion of a variable does not lead to a reduction in timing error, it is removed. This iterative process continues until the combination of variables that produces the lowest forecast error is identified.

We also introduce short-term forecasting, recognizing that forecast accuracy typically declines over longer horizons. Instead of predicting all phases in the cycle, short-term forecasting focuses only on the next phase shift. We evaluate forecast accuracy within each of the four phases to evaluate how timing error improves. In this approach, the model is trained using data up to the most recent completed phase shift, then tested on the remaining period to evaluate the accuracy of the upcoming phase prediction. For instance, when forecasting the *Peak Transition* phase, the model is trained up until the end of the preceding *Expansion* phase and then tested on the subsequent data. Table 6 shows the split date of train and test sets in forecasting each upcoming phase.

Table 6: Testing Data Begin Date

Phase	**Split Date**
Expansion	Jan 2020
Peak Transition	July 2020
Contraction	July 2021
Trough Recovery	June 2022

4 Results

In this chapter, we present the results of the research and their impact on the truckload market cycle. We begin by evaluating the results of the Granger Causality test (Section 4.1), followed by an analysis of the lag significance results (Section 4.2), and conclude with the long-term forecast (Section 4.3) and short-term forecast (Section 4.4).

4.1 Granger Causality

The Granger Causality test is used to determine relationships among spot rate, contract rate, and each independent variable. As discussed in Section 3.4.6, we only test an independent variable in the VAR forecasting model if it significantly (p-value <0.1) causes both spot and contract rates, and if spot and contract rates also cause each other in the presence of this variable, ensuring that all variables selected have statistically validated, bidirectional influence within the system.

Table 7 displays the results of the Granger causality test for both spot and contract rates. Statistically significant relationships are shaded in green:

- Dark green indicates $p \leq 0.01$
- Medium green indicates $p \leq 0.05$
- Light green indicates $p \leq 0.1$

Unshaded cells represent relationships that are not statistically significant and were not included in further modeling. The following provides an example of how to interpret the table. “Spot → Contract" column shows whether the spot rate Granger-causes the contract rate in the model. Similarly, the "X → Spot" column reflects whether the independent variable X (e.g., PPI, Truck Tonnage Index, etc.) significantly affects the spot rate. This same interpretation applies across all four columns.

Table 7 indicates that 12 of the 31 tested variables present significance across all four criteria and are therefore advanced to testing in the forecast VAR model.

Table 7: Granger Causality Test Results

Model	Dependent Variable		Independent Variable	Optimal Lag	Spot → Contract	Contract → Spot	X → Spot	X → Contract
1	Spot	Contract		12	0.00	0.00	-	-
2	Spot	Contract	Log (PPI)	12	0.00	0.00	0.00	0.00
3	Spot	Contract	Truck Tonnage Index	12	0.26	0.00	0.01	0.00
4	Spot	Contract	Merchant Wholesalers: Inventories to Sales Ratio	12	0.00	0.00	0.00	0.00
5	Spot	Contract	LTR	12	0.63	0.67	0.79	0.09
6	Spot	Contract	Log (Class 8 Backlogs)	12	0.00	0.00	0.00	0.01
7	Spot	Contract	Class 8 Build	12	0.00	0.00	0.25	0.00
8	Spot	Contract	Log (Class 8 Inventory)	12	0.00	0.00	0.00	0.00
9	Spot	Contract	Log (Class 8 Gross)	12	0.02	0.00	0.00	0.00
10	Spot	Contract	Log (Class 8 Cancel)	12	0.00	0.00	0.00	0.00
11	Spot	Contract	Log (Class 8 Net)	12	0.00	0.00	0.00	0.00
12	Spot	Contract	Class 8 Retail Sales	12	0.00	0.00	0.00	0.00
13	Spot	Contract	Routing Guide Depth	10	0.00	0.14	0.63	0.01
14	Spot	Contract	Log (Carrier Authority – Granted)	12	0.71	0.40	0.56	0.19
15	Spot	Contract	Carrier Authority - Revoked	11	0.79	0.17	0.50	0.27
16	Spot	Contract	Log (Carrier Authority – Reinstated)	12	0.84	0.00	0.01	0.55
17	Spot	Contract	Carrier Authority - Net	12	0.71	0.65	0.62	0.23
18	Spot	Contract	Carrier Authority - Active	12	0.91	0.53	0.29	0.49
19	Spot	Contract	Money Supply	12	0.68	0.03	0.28	0.59
20	Spot	Contract	M2 Money Supply	12	0.67	0.02	0.00	0.00
21	Spot	Contract	S&P Commodity Index	12	0.00	0.06	0.33	0.42
22	Spot	Contract	CRB Commodity Index	12	0.00	0.00	0.00	0.00
23	Spot	Contract	Commodity Index	12	0.00	0.00	0.02	0.00
24	Spot	Contract	Housing Starts	12	0.00	0.00	0.07	0.04
25	Spot	Contract	Industrial Production Index	12	0.85	0.00	0.07	0.00
26	Spot	Contract	Manufacturing New Orders Index	12	0.00	0.00	0.55	0.01
27	Spot	Contract	Manufacturing Purchasing Index	12	0.00	0.00	0.34	0.08
28	Spot	Contract	Freight Transportation Services Index	12	0.50	0.00	0.07	0.00

29	Spot	Contract	Advanced Retail Sales	12	0.73	0.00	0.07	0.00
30	Spot	Contract	U.S. No 2 Diesel Retail Prices	12	0.00	0.00	0.00	0.00
31	Spot	Contract	Trucking Ton Mile	12	0.38	0.00	0.07	0.00

4.2 Lag Significance

The optimal number of lags selected using the Akaike Information Criterion (AIC) is determined to be 11-12 months across the 27 combinations of variables tested. The results suggest that nearly a full year of historical data is necessary to effectively forecast future values, highlighting the importance of longer-term temporal dependencies in the truckload rate cycle. We find that short-term fluctuations are insufficient to properly predict the truckload market cycle and instead rely on year-long horizons to predict the future cycle.

In addition, we examine the most significant lags with the highest impact for each variable, as they reveal how many months it takes for change in the independent variable to affect spot and contract rates. Table 8 presents the most impactful lags of each independent variable on spot and contract rates. As an example, a one-unit increase in the Merchant Wholesalers: Inventories to Sales Ratio leads to the largest decrease in the spot rate, with a $13.50 reduction after an 8-month lag. The greatest impact on the contract rate occurs after four months, corresponding to a $0.80 decrease.

Table 8: Lags in Months and Coefficients

Model	Spot Equation Lag (Coefficient)	Contract Equation Lag (Coefficient)
Spot Rate	L1 (1.88) (Impact of change in spot at time t-1 to spot at time t)	L4 (0.54)
Merchant Wholesalers: Inventories to Sales Ratio	L8 (-13.5)	L4 (-0.8)
Log (Class 8 Backlogs)	L5 (8.7)	L4 (1.1)
Log (Class 8 Inventory)	L5 (-5.6)	L5 (-0.9)
Log (Class 8 Gross)	L5 (1.5)	L4 (0.3)
Log (Class 8 Cancel)	L5 (-0.5)	L8 (-0.1)

Log (Class 8 Net)	L5 (1.1)	L4 (0.2)
Class 8 Retail Sales (in 10K)	L5 (0.4)	L2 (0.06)
CRB Commodity Index (in 100s)	L5 (1.6)	L10 (0.1)
Commodity Index (Bloomberg) (in 100s)	L5 (3.4)	L2 (0.4)
Housing Starts (in 1M)	L7 (0.2)	L9 (0.02)
Log (PPI)	L6 (13.1)	L7 (6.7)
#2 Diesel Fuel ($/Gallon)	L6 (2.4)	L11 (0.2)

Focusing first on the spot rate from a lag perspective, Table 8 illustrates how long it significantly takes for changes in key indicators to impact the spot rate. Specifically, changes in the Merchant Wholesalers: Inventory to Sales Ratio take about eight months to affect the spot rate, while Housing Starts takes approximately seven months. Changes in the PPI and Diesel Prices impact the spot rate after about six months. The CRB Commodity Index, Bloomberg Commodity Index, and all Class 8 truck-related metrics exhibit an effect after five months. If these indicators begin to shift in sequence starting with Merchant Wholesalers: Inventories to Sales Ratio, followed by Housing Starts, then PPI and Diesel Prices, and finally the Commodity and Class 8 metrics, they may signal an upcoming change in the spot rate in the following months. This is a key insight as this framework provides foresight to the industry as these metrics begin to display behavior that likely indicates a change in spot and contract rates.

The strength of influence on the spot rate varies across different variables. For example, a one-unit increase in Merchant Wholesalers: Inventories to Sales Ratio is associated with a $13.50 decrease in the spot rate. While this effect size may appear large, it is important to recognize that the average value of the ratio is approximately 1.30, making such a shift highly unlikely in practice. Rather, this result highlights the variable's sensitivity to changes. Among the Class 8 truck indicators, a one percent increase in Class 8 Backlogs is associated with a $0.087 increase in the spot rate, indicating tightening truck capacity. Conversely, a one percent increase in Class 8 Inventory corresponds to a $0.056 decrease in the spot rate, likely reflecting an easing of supply conditions. Other Class 8 metrics also exhibit smaller but meaningful effects. A one percent increase in Class 8 Gross Orders and Class 8 Net Orders raises spot rates by $0.015 and

$0.011, respectively. Meanwhile, a one percent increase in Class 8 Cancel reduces spot rates by $0.005. Additionally, a $10,000 increase in Class 8 Retail Sales leads to a $0.40 increase in the spot rate. For commodity and macroeconomic indicators, a 100-point increase in the CRB Commodity Index leads to a $1.60 increase in spot rates (or $0.016 per point increase). The Bloomberg Commodity Index has a stronger effect, with a $3.40 increase in spot rates per 100-point rise (or $0.034 per point increase). A 1,000,000-unit increase in Housing Starts is associated with a $0.20 increase in spot rates. Similarly, a one percent rise in the PPI results in a $0.13 increase. Finally, a one dollar increase in Diesel Price leads to a $2.40 increase in spot rates, reflecting the direct cost impact on freight movement. The magnitude might seem big but standard deviation of Diesel Price over 12 years is only $0.79, therefore, $1 increase in Diesel Price is less common.

Examining contract rate from a lagged perspective, Table 8 shows that changes in each indicator take different amounts of time to impact contract rates. For example, a change in spot rate rates four months to transfer ton contract rate. Next, a change in the Merchant Wholesalers: Inventories to Sales Ratio takes about four months to impact contract rates, while changes in Diesel Fuel prices take up to eleven months. The PPI affects contract rates after a seven-month lag, and Housing Starts have a nine-month lag. Most Class 8 truck indicators influence contract rate within two to five months, except for Class 8 Cancel, which take about eight months. Notably, the CRB Commodity Index impacts contract rate after ten months, while the Bloomberg Commodity Index does so in just two months. Although both indices measure commodity markets, they differ in how they weight various industries, which likely explains the variation in their lag times.

From a magnitude perspective, the effects on contract rates are smaller compared to spot rates, which is expected given the more stable nature of contract pricing. A one-unit increase in the Merchant Wholesalers: Inventories to Sales Ratio is associated with a $0.80 decrease in the contract rate. Among Class 8 metrics, a one percent increase in backlogs leads to a $0.011 increase in contract rates, while a one percent increase in Class 8 Inventory results in a $0.009 decrease. Increases in Class 8 Gross and Class 8 Net orders by one percent lead to increases of $0.003 and $0.002 of contract rate, respectively. Class 8 Cancels slightly reduce contract rates by $0.001 per one percent increase. A $10,000 rise in Class 8 Retail Sales adds about $0.06 to the contract rate. For commodity and macro indicators, a 100-point increase in the CRB Commodity

Index corresponds to a \$0.10 increase in contract rates (or \$0.001 per unit), while the Bloomberg Commodity Index has a larger impact at \$0.40 per 100 points (or \$0.004 per unit). A 1,000,000-unit increase in Housing Starts leads to a \$0.02 increase. PPI has a more notable effect, with a one percent increase translating to a \$0.067 rise in the contract rate. Finally, a one dollar increase in diesel fuel prices adds about \$0.20 to contract rates.

4.3 Long-Term Forecast

To be included in the forecast model, a candidate variable must significantly Granger-causes both the spot and contract rates, and its inclusion must not eliminate the significant Granger-causality from spot to contract rate. The selection process resulted in twelve retained independent variables. For each, the VAR model generates a system of three equations—one for the spot rate, one for the contract rate, and one for the candidate variable (X_i). Table 9 provides a summary of all forecasting models tested, including the variables included in each configuration. For example, Model 2 includes Spot, Contract, and PPI. Each variable is forecasted using its own lags and the lags of the other two variables. However, while the PPI equation is estimated, it is excluded from our analysis as we only forecast spot and contract rates. This structure is consistent across the 27 models.

The analysis began with an in-sample long-term forecast. The model was trained on the first two truckload market cycles, from April 2012 to June 2020, and tested on the third cycle, from July 2020 to March 2025. Forecast performance was evaluated using mainly timing error coupled with MAPE. Timing error is the most important evaluation metric for this research's purpose, as it measures how many months the model deviates from the actual timing of phase transitions. However, as mentioned before, with this approach, we tradeoff robustness and the likelihood of overfitting for the specific purpose of this study.

Of all 27 long-term forecast model iterations. The second through sixth columns indicate which variables were included. All models contain both dependent variables (spot and contract rates) and the set of independent variables varies across iterations. The "Optimal Lag" column shows how many historical months of data the VAR model uses for forecasting. The subsequent four columns report the absolute timing errors (in months) between the forecasted and actual phase shifts during the COVID-19 Pandemic cycle (as illustrated in Figure 9) which include up to four phase shifts. The "Average Error" column represents the mean of these four timing deviations among *Expansion*, *Peak Transition*, *Contraction*, and *Trough Recovery*. A dash indicates that a model fails to produce a clear phase transition for one or more of the shifts and is therefore not considered a candidate for the best-performing model. We also calculate the standard deviation of the four timing errors to assess consistency. While we include MAPE for spot and contract forecasts, timing error remained our primary evaluation criterion to determine model effectiveness.

We focus first on the simple models that include no more than three variables. As shown in Table 9, the three single-variable models with the lowest average timing error are:

- Model 1 (Spot and Contract Rates), with an average timing error of 4.4 months earlier
- Model 7 (Spot Rate, Contract Rate, and Class 8 Cancel), with an error of 5 months earlier
- Model 12 (Spot Rate, Contract Rate, and Housing Starts), also with an error of 5 months earlier

We find that the model consistently forecasts phase shifts before they occur, indicating a positive timing bias. We then evaluate more complex models incorporating more than three variables. As shown in Table 9, we test multiple variable combinations. Among these, only Model 25 that includes Spot, Contract, Class 8 Backlogs, and Housing Starts achieves a low average timing error of 5.0 months, matching the performance of the best single-variable models.

The first independent variable with significant predictive power is Class 8 Cancel. We believe that Class 8 Cancel may serve as a strong indicator of market weakness, as buyers typically face financial penalties for canceling orders and are unlikely to do so unless they anticipate a substantial downturn. Similarly, Class 8 Backlogs are closely tied to operation and market conditions. During periods of extreme tightness, normal fleet capacity may be insufficient, resulting in a buildup of order backlogs. Housing Starts are a strong indicator of market conditions, which align with the insights from experts interview, likely because home construction tends to increase during periods of economic strength. The top four best performing models are bolded in the table.

Table 9: Vector Autoregression Forecasting Results

	Variables					Optimal Lag	Peak Transition Error	Contraction Error	Trough Recovery Error	Avg. Error	Std. Dev.	MAPE (Spot)	MAPE (Contract)
1	**Spot**	**Contract**				**12**	**0**	**7**	**6**	**4.4**	**3.8**	**17.6%**	**10.1%**
2	Spot	Contract	PPI			12	2	8	10	6.7	4.2	21.1%	11.9%
3	Spot	Contract	Merchant Wholesalers: Inventories to Sales Ratio			12	2	9	12	7.8	5.2	21.6%	12.7%
4	Spot	Contract	Log (Class 8 Backlogs)			12	2	8	9	6.4	3.8	15.9%	10.0%
5	Spot	Contract	Log (Class 8 Inventory)			12	1	6	12	6.4	5.6	11.9%	10.4%
6	Spot	Contract	Log (Class 8 Gross)			12	1	0	-	-	-	13.2%	8.9%
7	**Spot**	**Contract**	**Log (Class 8 Cancel)**			**12**	**1**	**7**	**7**	**5.0**	**3.5**	**19.9%**	**10.1%**
8	Spot	Contract	Log (Class 8 Net)			12	1	1	-	-	-	13.0%	9.1%
9	Spot	Contract	Class 8 Retail Sales			12	1	6	13	6.7	6.1	11.1%	8.6%
10	Spot	Contract	CRB Commodity Index			12	2	8	8	6.4	3.8	19.4%	11.4%
11	Spot	Contract	Commodity Index (Bloomberg)			12	2	8	9	6.4	3.8	17.8%	10.7%
12	**Spot**	**Contract**	**Housing Starts**			**12**	**1**	**7**	**7**	**5.0**	**3.5**	**20.6%**	**10.7%**
13	Spot	Contract	U.S. No. 2 Diesel Retail Prices			12	2	8	8	6.1	3.5	17.5%	10.6%

14	Spot	Contract	Log (Class 8 Cancel)	Housing Starts		12	1	7	8	5.4	3.8	23.2%	12.0%
15	Spot	Contract	Log (Class 8 Cancel)	U.S. No. 2 Diesel Retail Prices		12	2	8	9	6.4	3.8	28.3%	14.3%
16	Spot	Contract	Housing Starts	U.S. No. 2 Diesel Retail Prices		12	2	9	11	7.4	4.8	26.9%	14.6%
17	Spot	Contract	Log (Class 8 Inventory)	Log (Class 8 Cancel)		12	1	0	-	-	-	12.5%	8.8%
18	Spot	Contract	Log (Class 8 Backlogs)	Log (Class 8 Cancel)		12	2	9	13	8.1	5.6	25.6%	14.8%
19	Spot	Contract	Log (Class 8 Cancel)	CRB Commodity Index		12	1	7	9	5.7	4.2	24.1%	12.8%
20	Spot	Contract	Log (Class 8 Cancel)	Commodity Index		12	1	7	9	5.7	4.2	23.4%	12.3%
21	Spot	Contract	Log (Class 8 Cancel)	Class 8 Retail Sales		12	2	9	12	7.8	5.2	16.1%	10.6%
22	Spot	Contract	PPI	Log (Class 8 Cancel)		12	2	9	13	8.1	5.6	23.8%	12.4%
23	Spot	Contract	Merchant Wholesalers: Inventories to Sales Ratio	Log (Class 8 Cancel)		12	2	9	12	7.8	5.2	18.7%	11.3%
24	Spot	Contract	Log (Class 8 Inventory)	Housing Starts		12	3	9	-	-	-	24.4%	13.9%
25	**Spot**	**Contract**	**Log (Class 8 Backlogs)**	**Housing Starts**		**12**	**1**	**7**	**7**	**5.0**	**3.5**	**13.3%**	**9.3%**
26	Spot	Contract	CRB Commodity	Housing Starts		11	2	8	9	6.4	3.8	19.3%	11.5%
27	Spot	Contract	Log (Class 8 Cancel)	Commodity Index	Housing Starts	12	0	7	10	5.7	5.2	21.3%	12.5%

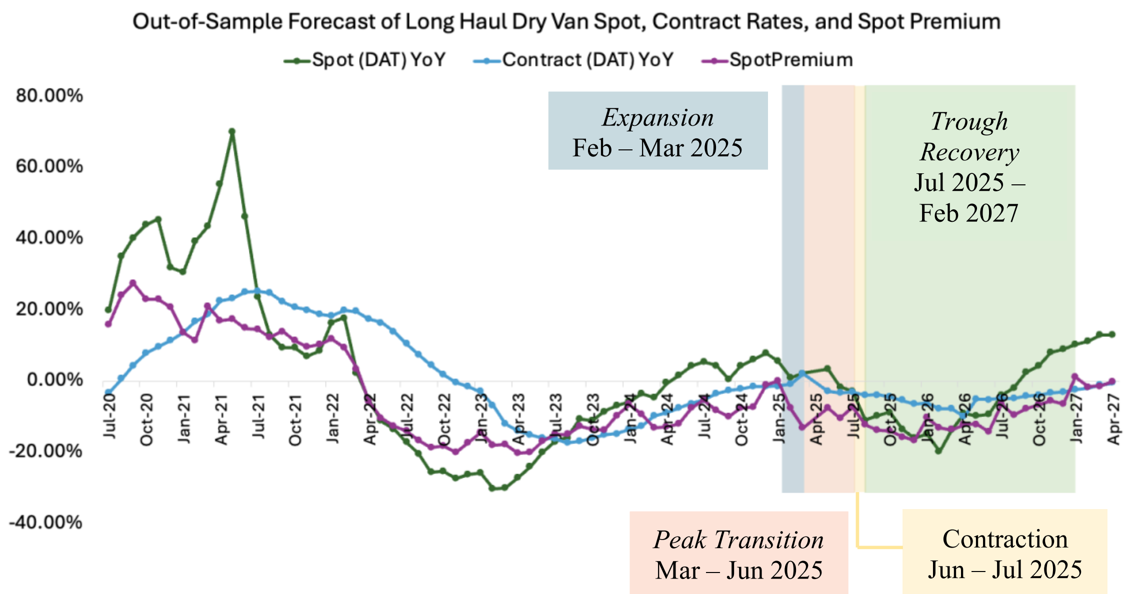
We conclude with an out-of-sample long-term forecast. In time series forecasting, shifting the training period can introduce variability in model outcomes, underscoring the need for thorough evaluation. As shown in Table 10, this variability can lead to three types of unexpected results in out-of-sample forecasts. Several models failed to produce clear cycle or phase shift transitions, including those incorporating spot, contract, and Class 8 Cancel; spot, contract, and Housing Starts; and spot, contract, Class 8 Backlogs, and Housing Starts. While not an exhaustive list, these examples highlight cases where forecasted YoY spot rate, YoY contract rate, or spot premium ratio do not demonstrate distinct inflection points. However, the model that included only spot and contract rates did produce identifiable phase shifts in its forecast.

Table 10: Out-of-Sample Forecast Patterns and Limitations of Best Performing Models

Out-of-Sample Forecast Patterns and Limitations	**Model**
Four phase shift crossings observed, but some phases are compressed	Spot and Contract
No phase shift crossings detected	Spot, Contract, and Class 8 Cancel
Erratic movements with excessive crossing points	Spot, Contract, and Housing Starts
	Spot, Contract, Class 8 Backlogs, and Housing Starts

Figure 12 shows the out-of-sample YoY spot rate, YoY contract rate, and spot premium ratio forecast for the model using spot and contract rates. February 2025 began the onset of the *Expansion* phase. The model also suggests that *Peak Transition* phase will occur in March 2025. *Contraction* will begin in June 2025. *Trough Recovery* will begin in July 2025 and end in February 2027 where the *Expansion* phase of the next cycle begins. In an effort to reduce random fluctuations in the forecast, we experiment using a three-month moving average smoothing technique on the outputted forecasted values but saw little impact to the timing of the phase shifts.

Figure 12: Out-of-Sample Forecast (Spot, Contract)



Comparing historical truckload cycle patterns with our forecast reveals notable differences. From 2013 to 2024, the average duration of full cycles was approximately 15.7 quarters, or 3.9 years. During this period, the average peak-to-trough amplitude in spot rate was \$0.85 per mile. In contrast to previous cycles, our forecast indicates that the upcoming cycle will be shorter, spanning approximately 2 years from February 2025 to February 2027. Notably, the first three phases in our forecast are significantly more compressed, lasting as little as one month — compared to historical norms where these phases typically lasted at least seven months. In terms of amplitude, the forecasted spot rate exhibits a more moderate change than historical rate of about \$0.40 per mile. A detailed discussion of the factors contributing to these variations is provided in Chapter 5.

However, a key takeaway from this research is the identification of three variables that significantly influence spot and contract rates: Class 8 Cancel, Class 8 Backlogs, and Housing Starts. Each of these metrics captures market sentiment in a forward-looking manner, indicating that the most critical indicators for analyzing the truckload market cycle are closely tied to the industry's and consumers' willingness to invest in long-term assets. This investment behavior is likely driven by realized or anticipated shifts in the broader economy, signaling transitions to tighter or softer market conditions and influencing the timing of capital expenditures.

4.4 Short-Term Forecast

While long-term forecasts provide a broader view of the whole cycle dynamics, they often come with reduced accuracy due to the extended forecast horizon. In contrast, short-term forecasts focus solely on predicting the next phase shift, trading breadth for improved precision. We conduct only in-sample forecasts for the short-term analysis, as the out-of-sample forecast would be identical to the long-term approach, just with a shorter horizon. Instead of projecting 24 months ahead, the short-term forecast focuses on the next phase shift. We run the same models as with the long-term forecast, but portion the training and test data split date so that the training data ends at the previous phase shift. For example, to forecast the *Expansion* of the COVID-19 Pandemic cycle, we train the model on data up to the *Trough Recovery* shift of the ELD Mandate cycle so that *Expansion* shift could be captured in the test set forecast.

Table 11 highlights the models with the lowest timing errors for forecasting each individual phase and their train set period. Within the test set, the short-term models show lower forecast errors, with zero-month error, where phase shifts predicted by our model to occur in the same month as the actual shifts. The lower forecast errors occur for two potential reasons. First, forecasting over a shorter horizon naturally reduces error. Second, as we predict the further phases, the training dataset expands, which improves model performance. However, selecting different models and variables for each phase risks overfitting, given only four phase shifts are available to evaluate forecast accuracy.

Each phase is influenced by a slightly different set of variables. Compared to the long-term forecasts, the short-term, phase-specific forecasts uncovered additional influential indicators. For *Peak Transition*, the CRB Commodity Index becomes an important driver. PPI, Merchant Wholesalers data, and the CRB Commodity Index play a more important role in forecasting *Contraction*. For *Trough Recovery*, U.S. No.2 Diesel Fuel is relevant. All four phases were predicted with zero timing error.

Table 11: Optimal Timing Error

Predicted Phase	Train Set	Models with Lowest Timing Error	Error (months)
Expansion	April 2012 – Jan 2020	Spot, Contract, Class 8 Backlogs, Class 8 Cancel	0
Peak Transition	April 2012 – July 2020	Spot and Contract	0
		Spot, Contract, Class 8 Cancel, CRB Commodity Index, Housing Starts	0
Contraction	April 2012 – July 2021	Spot, Contract, PPI, Class 8 Cancel, CRB Commodity Index, Housing Starts	0
		Spot, Contract, Merchant Wholesalers, Class 8 Cancel, CRB Commodity Index, Housing Starts	0
Trough Recovery	April 2012 – June 2022	Spot, Contract, Class 8 Cancel, US No. 2 Diesel Fuel	0

To mitigate the risk of overfitting, we calculate the average timing error across multiple short-term forecasts, shown in Table 12. We calculate the average timing error when the best-performing model for one specific phase is used to forecast all four phases. For example, if the model that performs best in forecasting the *Expansion* phase is applied to forecast *Peak Transition*, *Contraction*, and *Trough Recovery*, we assess the resulting average timing error across all phases. Table 12 shows the best performing models which generate lowest average timing error across the four phases forecasts. This approach avoids selectively assigning different models to individual phases, instead assessing the average timing error across the four phases.

Table 12: Short-Term Best Performing Models

Models with Lowest Timing Error	Avg. Error (months)
Spot, Contract	2
Spot, Contract, Housing Starts	2
Spot, Contract, Class 8 Backlogs, Class 8 Cancel	2
Spot, Contract, Class 8 Inventory, Housing Starts	2

Comparing Table 11 and Table 12, spot and contract rates, along with Housing Starts, Class 8 Backlogs, Class 8 Cancel, and Class 8 Inventory, demonstrate consistent performance across all phases in short-term forecasting. In contrast, variables such as the CRB Commodity Index, PPI, Merchant Wholesalers, and U.S. No. 2 Diesel Fuel tend to be more phase-specific and perform less reliably when applied to phases outside their strongest fit.

In conclusion, short-term forecasts are more effective for accurately and promptly identifying the next phase shift in the cycle, but they must be applied with caution. Similar to the long-term forecast, the short-term out-of-sample forecast does not clearly capture the defined phase changes.

5 Discussion

This research establishes an industry-informed definition of the truckload market cycle, identifies two dependent variables and key independent variables for forecasting, and presents a method for short- and long-term cycle prediction using a Vector Autoregression (VAR) model. Chapter 5 concludes this research by exploring possible implications for carriers, shippers, and brokers (Section 5.1), limitations (Section 5.2), and recommended future research (Section 5.3).

5.1 Implications

Anticipating truckload market cycle shifts and understanding the underlying dynamics of the cycle is critical for shippers, carriers, and brokers to adequately prepare for upcoming disruptions to their business including fluctuating spot and contract prices, changes in capacity utilization, and overall financial performance. Both shippers and carriers should be especially keen to implement this model during the Request for Proposal (RFP) and contract bidding processes to ensure contract agreements align with expected cycle dynamics and to determine optimal contract lengths. While market shocks are challenging to predict, managers should implement this model for scenario-planning purposes to prepare for unknown market turns and create risk mitigation and business continuity plans in order to proactively plan for these occurrences rather than react and suffer unintended consequences.

Carriers must anticipate changes in capacity to optimize network planning and maximize operational efficiency. This includes addressing deadhead miles and optimizing consolidation during *Contraction* and *Trough Recovery*, as well as securing additional capacity during *Expansion* and *Peak Transition*. Carriers may also find this forecast useful in determining appropriate times to rely on favorable spot market conditions and increase capacity. Conversely, carriers should monitor for market downturns to avoid investing in new fleets when the market is expected to loosen and excess capacity will be abundant.

Shippers should consider incorporating this model when establishing time-bound contracts with carriers. As market conditions tighten or loosen, static contracts can quickly become misaligned with prevailing spot rates. To maintain alignment with market dynamics, shippers may benefit from shorter RFP cycles or built-in flexibility to adjust contract terms during their lifespan.

Brokers should consider these findings in order to maintain positive relationships among shippers and carriers, as well as maximize revenue and profits. Because brokers secure capacity from carriers and sell it in real-time to shippers, brokers should react to expected changes in the truckload market cycle by securing capacity in an upward market (during *Trough Recovery* and *Expansion*). This ensures benefit for all parties as brokers will realize greater revenues, shippers will have available capacity to move their product, and carriers' fleets will be utilized.

Finally, establishing a single, industry-informed definition of the truckload market cycle enables stakeholders to align expectations, minimize miscommunication, and uniformly predict when phase transitions or new cycles are likely to occur. In conclusion, this framework is intended to benefit the entire FTL market, including shippers, carriers, and brokers.

5.2 Limitations

This research is not devoid of limitations derived from data, independent variables, and time constraints. We acknowledge these drawbacks and intend to provide a wholistic overview throughout this section. First, this study relies primarily on public data for the purpose of reproducibility. However, while our dependent variables (spot and contract rate) contain data from 2012-2025, some of the independent variables have more limited data and thus reduce the model's training data. Ultimately, lacking full datasets hinders the predicting power of future forecasts. Additionally, some data sets, including DAT's spot and contract rates, were obtained from personal communication and are therefore not available for public use without subscriptions to data providers.

Additionally, as described in Chapter 1, the Motor Carrier Act of 1980 deregulated the United States' trucking market. Before this time, the motor carrier industry was not market-driven and thus did not undergo traditional market cycles. A weakness of this research is that we can only evaluate three cycles given data availability. In addition, each truckload cycle begins with a "shock" or external factor that disrupted the industry causing the cyclical movement (i.e. ELD mandate, COVID-19 pandemic). The goal of this research is to predict upcoming cycles. While we might be able to predict the magnitude and timing of the impact after-market shocks occur, we cannot ascertain when future shock will arrive as they are random events. Moreover, we validated our model against the COVID-19 pandemic-era market cycle, which deviated notably from prior patterns. Unlike earlier cycles, the post-*Peak Transitio*n period during the

COVID-19 pandemic remained in a prolonged soft market, presenting a challenge for accurate forecasting. This divergence, particularly the extended duration of the *Contraction* and *Trough Recovery* phases, complicates predictions for the next 24 months. Given that our optimal lag structure relies on approximately one year of historical data, the long-term forecast remains influenced by the latter part of the COVID-19 pandemic cycle.

Although the VAR model effectively identified the most influential variables driving spot and contract rates and captured linear interdependencies across time series, our findings suggest that it is not best suited for long-term forecasting of truckload market cycles. While the model performed adequately on testing data, its out-of-sample predictive accuracy deteriorated in the post-pandemic period. This limitation is largely due to the VAR model's reliance on linear assumptions, which fail to capture the nonlinear dynamics introduced by unprecedented market disruptions. As a result, the model struggled to produce reliable forecasts beyond the structural shifts caused by the pandemic. Section 5.3 recommends additional research in this space to address these drawbacks.

5.3 Future Work

This research has many extensions that can and should be explored in future academic research. Here, we detail the most pertinent extensions. We focused our attention on linear models (i.e. OLS, ARIMAX, and VAR) to predict future market cycle shifts. However, we recommend future research to explore other types of models including Fourier, Sine and Cosine, and Harmonic models that evaluate the sinusoidal movements as seen in the past cycles. Additionally, we recommend exploring non-linear relationships within the data by applying machine learning (ML) models to assess whether multiplicative or exponential patterns are present. Random Forest, XGBoost, and Neural Networks are potential modeling choices to train and teach the model to forecast into the upcoming cycle. We also recommend an extension to evaluate regime switching modeling (i.e. Markov-Switching) in which the mean and variance of the data is not assumed to follow a normal distribution (Clower, 2021).

While we incorporated more than 30 independent variables into our research, we acknowledge the immense amount of additional data available that affects the truckload market cycle. We encourage future research to expand upon the independent variables chosen in our research to incorporate more economic and industry-specific metrics. To create a more userfriendly application, we suggest creating interactive dashboards for shippers, carriers, and brokers to understand the current state of the truckload market cycle and prepare for upcoming fluctuations. This type of tool may be used both in real-time planning as well as in scenario testing for unknown shocks such as a pandemic, hurricane, or other unforeseen event.

6 Conclusion

In conclusion, this research seeks to address a key question in the U.S. dry van FTL market: how can the truckload market cycle be defined, and how can future shifts between its phases be predicted? To address this question, we first engaged with industry experts to gather insights into the metrics they currently use to track the truckload market cycle. Building on these insights, we conducted an industry-wide survey to validate the most effective methods for tracking the cycle. Using this foundation, we developed an industry-informed definition of the truckload market cycle, dividing it into four distinct phases: *Expansion, Peak Transition, Contraction, and Trough Recovery*. We used spot rate, contract rate, and spot premium ratio as representatives of the market. We then constructed a Vector Autoregression (VAR) model to analyze relationship among independent variables versus spot and contract rates, using Granger Causality Test to detect these relationships. We found that metrics related to Class 8 indicators and certain economy-wide metrics have significant impact to spot and contract rates at different magnitude and time lags. We then forecasted both short- and long-term cycle movements using the VAR model and applied our cycle definition to predict the timing of future phase shifts. Even though forecasting truckload business cycle is inherently challenging, the variables that have shown significant impact on predicting spot and contract rates are Class 8 Cancel, Class 8 Backlogs, and Housing Starts. We offer this research to the truckload market community and hope it serves as a foundation for continued exploration in this critical field.

Appendices

Appendix A Industry Survey

This appendix outlines questions presented in industry survey and their responses.

Q1

Please select all metrics you use to determine how the market is performing. These metrics were frequently referenced by industry experts throughout an interview process.

> ATA - American Trucking Association
> BTS - Bureau of Transportation Statistics
> DAT - DAT Freight and Analytics
> FMCSA - Federal Motor Carrier Safety Administration
> FRED - Federal Reserve Economic Data
> FTR - Freight Transportation Research Associates

Metric	High Value	Medium/High	Medium/Low	Low Value	Do Not Use	Total Responses
DAT/Truckstop Spot Rates	52	29	16	8	5	110
DAT/Truckstop Contract Rates	56	26	9	10	11	112
DAT/Truckstop Load-to-Truck Ratio	21	35	30	10	14	110
Tender Rejection Rate	26	29	28	10	16	109
DAT/Truckstop Spot-Contract Rate Spread	30	36	17	9	16	108
Cass Freight Index	14	20	25	14	37	110
Class 8 Tractor Orders	10	10	22	23	43	108
FTR Active Truck Utilization	11	18	10	24	44	107
FMCSA Carrier Authority	17	12	17	27	35	108
C.H. Robinson Routing Guide Depth	6	4	21	11	65	107
ATA Truck Tonnage Index	5	6	24	22	50	107
BTS US Ton-Miles	4	5	7	11	81	108
FRED Personal Consumption Expenditure (PCE)	3	7	14	13	70	107
Other	9	11	6	1	19	46

Q2

Given the below definitions of the full truckload dry van market cycle, rank from most useful to least useful to make decisions for your business.

The TL market cycle is defined as a tight (expansionary) market when (1) _____, while it is defined as a loose (contractionary) market when (2) _____.

Option 1

(1) YoY percent changes in spot rates are positive for ≥ 3 consecutive months

(2) YoY percent changes in spot rates are negative for ≥ 3 consecutive months

Option 2

(1) The spot rate crosses and exceeds the contract rate

(2) The spot rate crosses and is below the contract rate

Option 3

(1) The tender rejection rate is increasing for ≥ 3 consecutive months

(2) The tender rejection rate is decreasing for ≥ 3 consecutive months

Option 4

(1) The revenue/profitability of publicly traded carrier companies (e.g., J.B. Hunt, Heartland Express, Knight-Swift) or independent smaller carriers is increasing for a sustained period

(2) The revenue/profitability of publicly traded carrier companies (e.g., J.B. Hunt, Heartland Express, Knight-Swift) or independent smaller carriers is decreasing for a sustained period

Q3

If you use a different definition of the truckload business cycle that wasn't included above, please state it here. (Optional)

Q5

Please select the most appropriate company classification(s) to which you belong. Select all that apply.

- ☐ Shipper with a Private Fleet
- ☐ Shipper without a Private Fleet
- ☐ Asset-Based Carrier
- ☐ Asset-Based Carrier with Broker

- ☐ Non-Asset-Based Broker
- ☐ Other: ____________

Q6

Please select the geographic region(s) you most predominantly work in. Select all that apply.

- ☐ North America
- ☐ European Union
- ☐ Asia
- ☐ South America
- ☐ Other: ____________

Q7

If you wish to receive updates regarding this research, please provide your name and email address. Providing this information is entirely optional. If you choose not to disclose this information, the survey will remain completely anonymous.

- First Name: _______________
- Last Name: _______________
- Company: _______________
- Email: _______________

References

Acar, K., Brogan, J., Pena, A. M., Sonthalia, B., Zimmerman, M. (2024). Waiting for the tide to turn. CSCMP's Annual State of Logistics Report, 2.

Acocella, A., Caplice, C., & Sheffi, Y. (2020). Elephants or goldfish?: An empirical analysis of carrier reciprocity in dynamic freight markets. *Transportation Research Part E: Logistics and Transportation Review*. https://doi.org/10.1016/j.tre.2020.102073.

ACT Research. (2023, February 19). *The Truckload Cycle: Demand Drivers of Freight*. https://www.actresearch.net/resources/blog/truckload-cycle-demand-drivers-of-freight.

ACT Research. (n.d.) *Market indicators*. https://www.actresearch.net/resources/us-freight-sector/market-indicators.

Bevans, R. (2023, June 22). *Akaike Information Criterion | When & How to Use It (Example).* Scribbr. Retrieved April 21, 2025. https://www.scribbr.com/statistics/akaike-information-criterion/.

Bloomberg Commodity Index (BCOM). (n.d.) https://assets.bbhub.io/professional/sites/27/BCOM.pdf.

BlueGrace Logistics. (2022, February 7). *Understanding Truckload Rates: Contract vs Spot*. bluegrace. https://www.citationmachine.net/apa/cite-a-website/custom.

Bobbitt, Z. (2021, November 29). *How to perform a Granger-causality test in Python*. Statology. https://www.statology.org/granger-causality-test-in-python/.

Bowman, R. (2013, November 5). *DOT's New Curb on Driver Hours Is Hurting Productivity, Truckers Charge*. Forbes. https://www.forbes.com/sites/robertbowman/2013/11/05/dots-new-curb-on-driver-hours-is-hurting-productivity-truckers-charge/.

Bureau of Economic Analysis U.S. Department of Commerce. (2024, February 28). *Gross Domestic Product, Fourth Quarter and Year 2023 (Second Estimate)*. bea. https://www.bea.gov/news/2024/gross-domestic-product-fourth-quarter-and-year-2023-second-estimate.

Cass Information Systems, Inc. (n.d.). *CASS Truckload Linehaul Index | CASS Information Systems*. https://www.cassinfo.com/freight-audit-payment/cass-transportation-indexes/truckload-linehaul-index#:~:text=The%20Cass%20Truckload%20Linehaul%20Index%20is%20an%20accurate%2C%20timely%20indicator,reflection%20of%20trends%20in%20baseline

Caza, G., & Shekhar, V. (2022, June 10). *Managing Disruptions: Understanding shipper routing guide performance*. Massachusetts Institute of Technology. https://hdl.handle.net/1721.1/142947.

Caza, G., & Shekhar, V. (2023, May 18). *Dealing with disruptions: Shipper Routing Guide Performance and tips for tendering in the "New normal."* MIT Supply Chain Management. https://scm.mit.edu/news-and-events/dealing-with-disruptions-shipper-routing-guide-performance-and-tips-for-tendering-in-the-new-normal/.

C.H. Robinson. (n.d.). *Key Insights for Guiding Your Transportation Strategy*. https://www.chrobinson.com/en-us/resources/resource-center/guides/key-insights-guiding-transportation-strategy/.

Clarksons. (n.d.). *What is spot shipping?* https://www.clarksons.com/glossary/what-is-spot-shipping/.

Clower, E. (2021, September 3). *Introduction to Markov-Switching Models*. Aptech. https://www.aptech.com/blog/introduction-to-markov-switching-models/#:~:text=Regime%20switching%20models%20are%20most,consider%20a%20regime%20switching%20model.

CRB Commodity Index. (n.d.). Trading Economics. https://tradingeconomics.com/commodity/crb.

Croke, D. (2023, April 25). *Understand the demand for what you haul*. DAT Freight & Analytics. https://www.dat.com/blog/understand-the-demand-for-what-you-haul.

DAT. (2025). *Company Timeline*. https://www.dat.com/company/history.

Dorf, P. (2016, September 8). *What is the Load-to-Truck Ratio?*. DAT Freight & Analytics. https://www.dat.com/blog/what-is-the-load-to-truck-ratio.

Federal Motor Carrier Safety Administration. (2017, October 17). *ELD Fact Sheet - English Version*. FMCSA. https://www.fmcsa.dot.gov/hours-service/elds/eld-fact-sheet-english-version

Federal Motor Carrier Safety Administration. (2024, April 19). *Types of Operating Authority*. (2024, April 19). https://www.fmcsa.dot.gov/registration/types-operating-authority.

Federal Reserve Bank of St. Louis. (n.d.). *Federal Reserve Economic Data*. FRED. https://fred.stlouisfed.org/.

Ford, C. (2018, August 17). *Interpreting Log Transformations in a Linear Model*. University of Virginia. https://library.virginia.edu/data/articles/interpreting-log-transformations-in-a-linear-model#:~:text=Why%20do%20this%3F,the%20context%20of%20linear%20modeling.

Hampstead, J. P. (2025, January 27). *The trucking market is still headed in the right direction*. FreightWaves. https://www.freightwaves.com/news/the-trucking-market-is-still-headed-in-the-right-direction.

Hayes, A. (2022, April 27). *S&P GSCI definition, commodity types listed, potential drawbacks*. Investopedia. https://www.investopedia.com/terms/g/gsci.asp.

Huang, C., & Petukhina, A. (1970, January 1). *Exploratory time series data analysis*. SpringerLink. https://link.springer.com/chapter/10.1007/978-3-031-13584-2_2#Sec7.

IBISWorld Industry Reports. (n.d.). *Freight Transportation Services Index*. https://www.ibisworld.com/us/bed/freight-transportation-services-index/112652/#:~:text=The%20US%20freight%20transportation%20services,waterway%2C%20pipeline%20and%20airfreight%20carriers.

Jimoh, A. (2023, December 14). *Why is the vector autoregressive model one of the best for Time-series forecasting?*. Medium. https://medium.com/%40aliyujimoh58/why-is-the-vector-autoregressive-model-one-of-the-best-for-time-series-forecasting-317649670ea1.

Katzman, D., Moreno, J., Noelanders, J., & Winston-GalantLib, M. (n.d.). *10.4: Using Eigenvalues and Eigenvectors to Find Stability and Solve ODEs*. LibreTexts Engineering. https://eng.libretexts.org/Bookshelves/Industrial_and_Systems_Engineering/Chemical_Process_Dynamics_and_Controls_(Woolf)/10%3A_Dynamical_Systems_Analysis/10.04%3A_Using_eigenvalues_and_eigenvectors_to_find_stability_and_solve_ODEs.

Kopp, C. M. M. (2024, June 28). *ISM manufacturing index: Definition and how it's calculated*. Investopedia. https://www.investopedia.com/terms/i/ism-mfg.asp.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). *Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?*. Science Direct. https://www.sciencedirect.com/science/article/abs/pii/030440769290104Y?via%3Dihub.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Springer Nature Link. https://link.springer.com/book/10.1007/978-3-540-27752-1.

Majestic Steel USA. (n.d.). *How ISM new orders index increases visibility into market action*. https://www.majesticsteel.com/ism-new-orders/#:~:text=What%20is%20the%20ISM%20New,shows%20a%20decline%20in%20orders.

McBride, B. (2024, June 4). *Understanding Shipping Contracts*. Zero Down Supply Chain Solutions. https://www.zdscs.com/blog/understanding-shipping-contracts/.

Miller, J. (2024). *The trucking ton-mile index reading for July should put a damper on anyone expecting a recovery of trucking volumes in*. [Post]. LinkedIn. https://www.linkedin.com/posts/jason-miller-32110325_supplychain-supplychainmanagement-shipsanshsipping-activity-7108058048262258689-WQam/?utm_source=share&utm_medium=member_desktop.

Miller, J. (2024, December 11). *First-half 2025 dry van truckload outlook: Improving conditions ahead*. Supply Chain Management Review. https://www.scmr.com/article/first-half-2025-dry-van-truckload-outlook-improving-conditions-ahead.

Miller, J., & Bolumole, Y. (2022). The Trucking Ton-Mile Index: a new way for measuring trucking activity in the United States.

Miller, J. W., Scott, A., & Williams, B. D. (2020, September 16). *Pricing Dynamics in the Truckload Sector: The Moderating Role of the Electronic Logging Device Mandate*. Wiley Online Library. https://onlinelibrary.wiley.com/doi/10.1111/jbl.12256.

Morgan, J. (2024, January 22). *Business cycles, trucking economics and how it all impacts your fleet*. Fleet Equipment Magazine. https://www.fleetequipmentmag.com/business-cycles-trucking-economics/.

Penn State Eberly College of Science. (n.d.-a). *Decomposition Models*. PennState: Statistics Online Courses. https://online.stat.psu.edu/stat510/lesson/5/5.1?utm.

Penn State Eberly College of Science. (n.d.-b). *Vector Autoregressive models VAR(p) models*. PennState: Statistics Online Courses. https://online.stat.psu.edu/stat510/lesson/11/11.2.

Pickett, C. (2018, May 4). *Navigating the US Truckload capacity cycle: Where are freight rates headed and why?*

Rajab, K., Kamalov, F., & Cherukuri, A. K. (2022). Forecasting COVID-19: Vector Autoregression-Based Model. *Arabian Journal for Science and Engineering*, *47*(6), 6851–6860. https://doi.org/10.1007/s13369-021-06526-2

RXO. (2025). *Q1 2025 Truckload Market Forecast: Spot & Contract Rate Trends*. RXO. https://rxo.com/resources/research/us-truckload-market-guide/#Download.

RXO. (n.d.-a). *Spot vs. Contract Rates: What's the Difference in Truckload Freight Shipping?* https://rxo.com/resources/shipper/contract-vs-spot-rates/.

RXO. (n.d.-b). *What is a Truckload Market Cycle? Learn the 7 Stages (With 3 Infographics)*. RXO, Inc. https://rxo.com/resources/research/truckload-market-cycle/.

Shojaie, A., & Fox, E. B. (2022, March 7). *Granger causality: A review and recent advances*. Annual Review of Statistics and Its Application. https://www.annualreviews.org/content/journals/10.1146/annurev-statistics-040120-010930#right-ref-B56.

SONAR Knowledge Center. (2024, May 23). *Tender rejection (TRI).* https://knowledge.gosonar.com/resources/sonar-data/trucking/tender-rejection-tri/.

StataCorp LLC. (n.d.). *Varstable - check eigenvalue stability condition*. https://www.stata.com/manuals/tsvarstable.pdf.

Statsmodels. (2023, October 3). *Statsmodels.tsa.seasonal.seasonal_decompose*. statsmodels. https://www.statsmodels.org/stable/generated/statsmodels.tsa.seasonal.seasonal_decompose.html.

U.S. Bureau of Labor Statistics. (n.d.). *Producer Price Indexes*. https://www.bls.gov/pPI/.

U.S. Energy Information Administration (EIA). (n.d.). *Gasoline and diesel fuel update*. https://www.eia.gov/petroleum/gasdiesel/.

U.S. Government Accountability Office. (1981, June 18). *Status and Impact of the Motor Carrier Act of 1980*. GAO. https://www.gao.gov/products/115670#:~:text=Highlights,a%20higher%20price%20for%20service.

Williams, L. (2025, January 28). *What Does a Freight Broker Do? (With Requirements)*. indeed. https://www.indeed.com/career-advice/careers/what-does-a-freight-broker-do.

Zivot, E. (n.d.). *Vector Autoregressive Models for Multivariate Time Series*. Welcome to Eric Zivot's UW Homepage. https://faculty.washington.edu/ezivot/econ584/notes/varModels.pdf.