Relationship between Price and Performance: An Analysis of the US Trucking Market

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Abstract

This thesis focuses on the study of the carrier-shipper relationships in the US trucking market. It uses data provided by a leading third party logistics (3PL) company to explore and determine whether a relationship exists between the prices charged by the carriers and the performance that they provide to the shippers. The performance metrics defined in the thesis are measured in three dimensions: on time pick-up, on time delivery, and acceptance ratio. The research uses ordinary least square (OLS) regression to study the effect of the performance parameters on the cost per load of a shipment. The research demonstrates that there is a mild relationship between on time delivery performance and price. With increase in on-time delivery performance, the price increases till a threshold is reached, beyond which it stabilizes. We found that a relationship exists between on-time pick-up and delivery. Since carriers who pick up late are able to deliver on time 80% of the times, the research could not find a direct relationship between on-time pick-up and price. The research also found that increased lane loyalty from a shipper to a carrier can lead to lower rates.

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-Nane

I dedicate my portion of the thesis to my late grandfather whose love for life and knowledge continues to inspire me to this day.

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-Sharmi

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We would also like to thank the members of our sponsor company, especially Steve Raetz, Kevin McCarthy, Glenn Koepke, and Guilherme Veloso. They were always available and ready to answer any questions we had and to share their knowledge and experience with us.

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1. Introduction

Transportation is the lifeblood of the U.S. economy, and over-the-road transportation is its major segment. The majority of freight movement, a critical element of business among firms, occurs through over-the-road trucking. In 2014, the economy depended on trucks to move about 70% of all the freight tonnage. To move about 10 billion tons of freight, more than 7 million people and 3 million truck drivers were employed (ATA, 2015).

There is a common belief in business that if you provide better service, you will receive a higher price. The converse is also believed to be true, that is the higher price you pay, the better the service you will receive. In short, the common perception is that a positive correlation exists between price and performance. Our research aims to test this belief and determine whether it holds true in the US Truckload (TL) transportation market.

Our research focuses on over-the-road dry van (TL) transportation market, where the main players are the shippers, carriers and third party logistics providers (3PLs). In this market shippers generally create the demand for TL services by offering large volumes of freight for transportation. To transport their goods they choose between having a private fleet and hiring external firms (for-hire carriers). Private fleets and for-hire carriers almost equally share the freight transportation spending in the industry (S&P 2014). In addition to asset based carriers, there are 3PLs that are non-asset based logistics providers that act as brokers, matching shippers' transportation demand with carriers' capacity. Our thesis analyzes historical data of shipping rates and performance provided by C.H.Robinson, a leading 3PL provider in the industry.

As a part of their business together, shippers and carriers enter into one to two years contracts. The terms of the contract are indicated in the routing guide. A routing guide is an electronic catalogue that includes the list of carriers with their corresponding prices. Everyday shipments are managed by this routing guide. The price that a shipper pays to the carrier is the total rate charged by a carrier for a particular load/shipment offered by a shipper. It includes line haul, fuel surcharge and accessorial costs and is charged on a per load basis. Both line haul rate and fuel surcharge are calculated based on the miles driven.

The objective of our research is to determine whether there is a correlation between the price that the shippers pay and the level of service that the carriers provide. It explores the relationships between carriers and shippers in the industry and tries to reveal the motivations behind their decisions. In the process of meeting their customers' expectations both carriers and shippers make important decisions to do business together. This thesis seeks to examine to what extent these decisions are connected with the common belief that higher price leads to better performance and vice versa.

This research will be beneficial for both carriers and shippers and will hopefully improve shipper-carrier relationships by facilitating a better understanding of each other's motivations. It will add more transparency in the shipper-carrier relationships by helping them have better expectations from each other about price and service levels.

The next section will introduce a more detailed overview of the research question and carrier performance.

1.1 Research Question

As the economy improved in 2013 and 2014, the demand for truckload carriers increased and the shippers started competing for reliable and high performing carriers. In such a situation, knowledge about a correlation between performance and the price will help the shippers make more prudent decisions about selecting carriers. The research will help the shippers eliminate uncertainty and costs arising from poor performance levels of certain carriers. By assessing the price levels, shippers will have better expectations about the carriers' service levels. Thus, price could act as an indicator of the performance. Shippers will also be able to become more consistent in their own commitments to their customers using the price as an indicator of the performance. Finally, shippers will have more visibility and opportunity to eliminate costly steps from their value chain.

The research will be beneficial for the carriers too. It will help carriers set right pricing strategies in accordance with their level of performance. Information about a correlation between service and price will give carriers opportunity to increase their revenue, maintain their customers (shippers) and stay competitive by improving their performance.

Currently both shippers and carriers are unaware of a proven relationship between the performance and the price. The output of this research will help in further solidifying shipper-carrier relationships and will help create the terms needed in a long term contract. It will also help reduce the overall inefficiencies in the industry associated with higher costs and with lower performance levels and thus, will improve the overall value proposition for both carriers and shippers.

1.2 Carrier Performance

Carrier service level plays a major role in maintaining existing shippers and attracting new shippers. Service level reflects the combined effect of different performance parameters. There is not a single performance metric, but rather a set of metrics. In other words, the performance criteria are multidimensional. These criteria include time reliability (on time delivery and pick up), technical competencies, flexibility during emergencies, willingness to share information, freight damage history, carrier financial stability, and total transit time. These factors are considered as the most important ones among shippers in the trucking industry (Coyle, Langley, Gibson, & Novack, 2008). For our research we will focus on performance factors describing timeliness and dependability of the carriers. The parameters we will consider are on time pick-up (OTP), on time delivery (OTD), and acceptance ratio (AR). These measures are the three major parameters describing service level that could be unveiled from our data.

OTP and OTD are measures of performance related to timeliness. They are binary variables that show whether a particular load was picked up or delivered on time. For our analysis we will aggregate OTP and OTD over the time and develop parameters called OTPPercent and OTDPercent that explain performance over a period of time for a particular carrier-shipper relationship. OTPPercent and OTDPercent are defined as the fraction of the loads picked or delivered on time from all the loads handed by the carrier. Acceptance Ratio (AR) is a performance parameter that considers the loyalty of the carriers. It shows how loyal a carrier is towards a shipper and is defined as the fraction of loads accepted by the primary carriers from total number of loads offered.

Our research tests the change in performance with respect to rates offered by the carriers.

It also seeks to test whether there is any relationship amongst the performance parameters themselves.

In addition, we will consider a factor called shipper loyalty, which is defined as the consistency with which a shipper offers loads to a carrier on a particular lane. We will test its effects on the cost per load and on the acceptance ratios. Thus, we will see whether a shipper loyalty on a lane towards a carrier inspires the same from a carrier towards a shipper.

This thesis is organized in the following manner. Chapter 2 provides a review of the relevant literature. Chapter 3 describes the dataset used for the analysis. Chapter 4 describes the analytical tools and results of the models used for the study. Chapter 5 provides the final insights, conclusion and further research that could be pursued on this subject.

2. Literature Review

This chapter provides an overview of the past research related to this thesis. First, it presents the factors influencing the price and introduces the different views on concept of carrier performance. Listing the results of past studies, this literature review shows how the different types of performance measurements were chosen to rate the carriers and the impact of these performance parameters on truckload pricing. It then summarizes the existing views on the relationship between price and performance. In the end, it presents the gaps in the existing literature and the insights that this research aims to provide.

2.1 Factors driving pricing

Different factors affect the truckload rates and many models have been defined that attempt to explain the changes in rates. Among the common factors mentioned in the literature are shipment volumes, tender rejections, carrier proximity, and network balance. Other factors mentioned are the market shifts, collaboration with 3PLs, and lead time. The detailed description of each of these factors is presented below.

Kafarski and Caruso (2012) examines the change in pricing caused by four different factors: shipment volume, tender rejections, carrier proximity, and network robustness. This study shows that an increase in the shipment volume could cause the prices to increase by 30-40% compared to the rates contracted originally with primary carriers. As for tender rejections, an increase in tender rejection, also causes an increase in prices. The research shows that the first rejection causes a price escalation of 6% on an average. The tenth rejection usually causes a 26% price escalation over the originally contracted rate with the primary carrier. However when considering all the rejected shipments, on an average the prices increase by 13% over the originally contracted rates. This research also develops a carrier proximity study according to which distance from carrier location to pick up or delivery location can have a large impact on pricing for short haul shipments. Finally, this research examines the impact of network robustness on prices. Network robustness is defined as the ability of the network to react to fluctuations in demand without a large impact on carriers and shippers. The study concludes that on lanes with robust networks, the prices increase slowly and remain in the same range. So regardless of the changes in demand, robust networks provide enough capacity to cover the volume at a price contracted originally. In other words, network robustness is considered a vital factor in maintaining stable prices.

Armstrong (2009) also addresses the role of volume and carrier's network as factors affecting pricing. This study mentions that volume is important only up to a certain threshold and after that, higher volume will not necessarily cause price reductions. An important factor is how the business offered by the shipper fits the carrier's operating network. Loads with certain lane, freight, and shipment specifications that fit well with the carrier's network, are generally favored by the carriers. Here, lane balance is mentioned as a major driver of pricing levels as it plays a role in generating optimal revenues for the carriers. This gives us an insight that we should use geography as a factor while developing base models for our analysis.

This same paper argues that the model that shippers should consider while trying to reduce their truckload pricing, and hence their transportation costs, is the carrier operational cost based model. In this model, the different categories of costs for a trucking company such as variable, semi-variable and fixed costs are analyzed. The author of this white paper argues that the shippers can help reduce the sum of the variable and the semi-variable costs by improving their own vendor management practices and understanding how the transportation lanes and the product mix of a shipper affects the carrier's costs and thus affect carrier pricing. This will help the shipper reduce his own transportation costs.

An interesting viewpoint mentioned in this same paper refers to the role of 3PLs in reducing transportation costs. Particularly, the author argues that 3PLs have information about multiple carriers' lanes and can thus, balance their networks leading to lower carrier network cost. This will further lead to price reductions for their customers (shippers) as well.

Another white paper published by C.H.Robinson Worldwide Inc. (2013) again considers network balance (mentioned in earlier studies) as a factor affecting pricing. The author argues that the shippers who provide volumes along the routes that result in network balances for a carrier will get charged lower rates compared to the ones that provide loads which result in network imbalances. The author shows this using historical rate curves over volumes in different geographies. He illustrates with an example that a shipper that requires a carrier to ship in low volume lanes which results in excessive empty miles and hence a less profitable proposition for the carrier will be charged at spot market rate. However, if a shipper understands the carrier's network and offers to bundle lower volume lanes within larger origin and destination pairs, it will be offered a more attractive freight rate.

This same research also mentions transportation market fluctuations as another factor impacting pricing decisions. During these market shifts some carriers will cancel existing contracts and turn to higher-paying freights. Here the good relationships with carriers will help the shippers. If the shippers have good relationships with the carriers and adjust to changing rates in market, they will be able to keep carriers from moving away and ensure adequate capacity for themselves. Thus, if there is a capacity shortness accompanied with high shipment volumes, the shippers will pay higher rates.

A study analyzing the correlation between price and tender lead time has been done (Caldwell and Fisher, 2008). Tender lead time is defined as the amount of time between when a load is tendered to a carrier to when the load needs to be picked up. The research concludes that lead time has a substantial impact on transportation cost in addition to other variables used in the model. The study suggests that even though the transportation costs are mainly affected by baseline factors and the impact of tender lead time on costs is very low, policy changes related to tender lead time is still a potential opportunity for cost savings for the shippers. The shippers can capitalize on this fact and attain savings if they employ improved business policies related to lead time. Particularly, this study shows that shippers have very distinct business policies with regard to lead time. The lead time offered to the carriers by the best customer is more than five days on average while it is less than a day for the worst shipper. This difference in lead time translates to an estimated cost penalty of $42 per load. It is important to note that the customer (shipper) with the worst lead time who shipped 8500 loads the previous year as mentioned in the study, paid $323,000 more for the same movement than the customer with the better lead time. Thus, adopting better lead time policies shippers will save considerable amounts of money.

2.2 Perspectives on Carrier Performance

There are views in the literature suggesting the price as the first important factor in carrier selection; however there are also many views suggesting that service level and performance parameters are more important than the price. Early studies on carrier selection, such as Cook (1967) regarded transportation cost as the most important criterion in carrier selection. Similarly, Murphy and Dalenberg (1991) considered flexible rates and shipment traceability more important than other factors. A recent research, conducted among 793 logistics professionals who specialized in purchasing LTL services, indicated freight rates as very important. When asked to rate 15 attributes of importance, 97% of the participants ranked the freight rates as first, calling them as extremely important (RBI, 2008).

Literature shows that identifying carrier performance parameters has motivated a large amount of research. In the past decade about thirty performance criteria have been recognized by different researchers. For example, Whyte (1992) developed thirteen criteria for measuring carrier performance. Among these criteria the most common ones were the reliability of on time pickup and delivery, computer link between shipper and carrier, and the carrier's awareness of the shippers' needs.

Among all these criteria discussed in the literature time reliability has received large attention by the researchers. For example, according to Varma (2008) time reliability is of key importance to shippers. "Just-in-time" delivery is vital in the reduction and elimination of warehousing and storage costs. Shippers schedule freight movements by considering travel delays and peak period congestion, with the aim of reducing their impact. Not surprisingly, predictable travel times have been considered more important than average travel times in a number of reports.

Voss, Page, Thomas, Keller, & Ozment, (2006) in their research used two techniques to determine the key factors that influence the tendering decision made by the shippers. One of the techniques was to get key personnel from the freight buying team at different shipper organizations to fill out a survey. The survey showed that contrary to popular belief, rates are not the most important factor that shippers consider while making the purchase decision. Shippers consider rate only second to delivery reliability. The team also tried to assess the extent to which a purchasing agent perceives possibility of career advancement on selection of a carrier possessing a particular criteria. Their research method showed that the purchase intention of the respondent to choose a carrier with most reliable delivery times is not correlated to the buyer's belief that it will lead to career advancement. This shows that delivery reliability is an order qualifier and is expected of all carriers. Factors like highest equipment availability and fastest complaint follow up were viewed as important to a purchasing agent from the point of view of his own career advancement and hence were more important to his purchasing decision.

Another study, considering time element as a reliability attribute, was done by Figliozzi (2004). The study indicates a growing trend in the truckload market of Time Definite Freight (TDF), which is defined as any shipment required to arrive within very tight time windows. The time delivery window may be overnight or within a certain number of days. The delivery window may be a full day on a particular date or may be defined as deliver by time, which specifies the latest delivery time within the day (e.g. by the beginning (9AM) or the end (5PM) of the business day). Alternatively, an exact window of delivery time (e.g. between 2PM and 4PM) may be specified.

Similarly, the pickup schedule defines the time frame in which the carrier will pick up the shipment.

Zsidisin, Voss, & Schlosser (2007) discussed three important performance measures, one of them again relating to time element. They have found that shippers usually maintain score-cards for three important metrics – On Time delivery performance, declined freight and dropped trailers. Usually transportation performance is considered "on-time" if the shipment arrives before or at its appointment time. Declined loads measures the percentage of loads accepted by a carrier on a shipper's initial tender. Dropped trailers are a measure of the number of trailers a carrier has pre-positioned at the shipper's facilities compared to the number of loads a carrier is pulling from the shipper's facilities.

Cheng (2009) contains somewhat different results on the preference of key performance parameters. It is worth mentioning that this research was done examining the Chinese transportation market. In her findings, criteria such as time, reliability, and flexibility, received very low ratings by the shippers. Cheng (2009) attributes this findings to the fact that trucking in China is considered superior to other modes in meeting these criteria. She mentions that this is one reason that it is the shippers' preferred mode in China. Meanwhile, the criteria which received higher ratings were the following: "Quality of Driver", "Cargo Handling Capability", "Carrier's Response to Emergency Situation", and "Shipment Tracking and Tracing Ability". In summary it is worth mentioning that shippers in US generally give more value to service overall than to cost in choosing carriers (Cheng, 2009).

2.3 Price and Performance correlation

While reviewing the literature, we came across several studies which examined the correlation between the performance and price. In these studies, among the performance parameters discussed were on time pickup, on time delivery, and tender rejection rates. In our research, we have looked at acceptance ratio as a measure of reliability. Acceptance ratio is complementary to the tender rejection rates. While tender rejection rate explains the percentage of the offered loads that a carrier rejected, acceptance ratio explains the percentage of the offered loads that a carrier accepted. In our research we will test the influence of acceptance ratios on truckload pricing.

Liu (2009) explores the correlation between customer service level and TL price in cold chain transportation. To measure customer service level she categorizes performance metrics into two categories: on time pickup and on time drop-off. Additionally, she aims to find out whether there is any relationship between cold chain quality (temperature performance) and customer service level. In her study the price is defined as the shipping cost that a carrier charges from the shipper. The study found no correlation between shipping cost and customer service level or between shipping cost and temperature performance. However, there was a correlation between customer service level and cold chain quality (temperature performance). Thus, carriers who perform well in customer service, generally also perform well in delivering temperature quality. An interesting insight of this study is that high-performing carriers are not necessarily charging high rates and even charge less than the average-performing carriers do. For the shipper, it is perfectly possible to find a carrier performing well in both on-time service and temperature with reasonable or even low rates. Moreover, there are several carriers charging very high rate, while providing very low level of service in both cold chain quality and on time pickup and delivery. This difference gives the shippers reasons to use carriers who are both "good" and "cheap". Giving such carriers higher volumes will be more beneficial as they can get even cheaper rates from economies of scales, (Liu, 2009).

By using ordinary least square (OLS) regression, Kim (2013) finds a relationship between a shipper's average truckload prices and the tender rejection rates. He concludes that tender rejection mostly generate increases in price. This finding is similar to the finding by Kafarski and Caruso (2012). Research by Kim (2013) also suggests a potential trade-off between price and tender rejection and shows that for the length of haul within 100-250 mile range, the lanes in the range of high rejection rates are accompanied with lower average truckload prices than the lanes with zero or near zero rejection rates. This means in the short haul (between 100-250 miles), there is a positive correlation between acceptance ratio and average truckload prices.

2.4 Summary

The research conducted so far has not shown whether on time pickup, on time delivery, and acceptance ratio impact the rates for over-the-road dry van TL transportation and if they do, how they impact the rates. The literature contains studies that explore the relationship between price and performance using such performance parameters as tender rejection or explore the relationship in a different transportation field such as cold chain transportation. Particularly, Kim (2013) and Kafarski and Caruso (2012) find a relationship between a shipper's average truckload prices and the tender rejection rates. Liu (2009) shows that there is no correlation between the performance measures and price in cold chain transportation.

The aim of our research is to add to the existing literature by examining and testing whether on time pickup, on time delivery and acceptance ratio have any impact on the freight rates for over-the-road trucking. The research output will help carriers understand which selection criteria influence the shippers' choice of carriers. The research will cover the gap that exists between offered and expected service levels and between generated and expected revenues by the carriers. Our research will investigate and demonstrate which attributes are really important to shippers. The results will put both carriers and shippers at advantage and improve shipper-carrier relationships by facilitating a better understanding of each other's motivations.

3. Dataset and Methodology

In this chapter, we will review our dataset and describe the truckload transportation network presented in the dataset. We will then describe the three metrics we have used to measure the performance of the carriers with respect to the shippers. We will also see the nature and the behavior of these metrics with respect to different shippers and lanes.

3.1. Understanding the Dataset

The dataset for this research consists of 27 months of tender and shipment records for dry-van, truck load shipments from the Transportation Management Centre (TMC), a staffed transportation management service, at C.H.Robinson (CHR), the largest third party logistics provider in the United States. The dataset includes tender information from 40 shippers and 963 carriers, operating within the 48 states of the United States. There were a total of 1,723,692 offers by the shippers to secure trucks for 807,662 shipments.

We cleaned the data and excluded loads that have the following characteristics:

- Length of Haul < 250 miles and Length of Hauls > 3000 Miles
- Cost per mile < $ 0.7 /mile and Cost per mile > $ 3.5/mile
- All loads with destination outside the United States
- Loads with missing values for customer and carrier identities
- Shippers who do not have loads across 8 quarters in the 24 months of data

Also, we analyzed the volume of the loads tendered by the shippers. From Figure 1, we can see that 10 shippers offered 85% of the total number of loads represented in the data. Hence, we decided to focus on these 10 shippers for advancing our analysis.

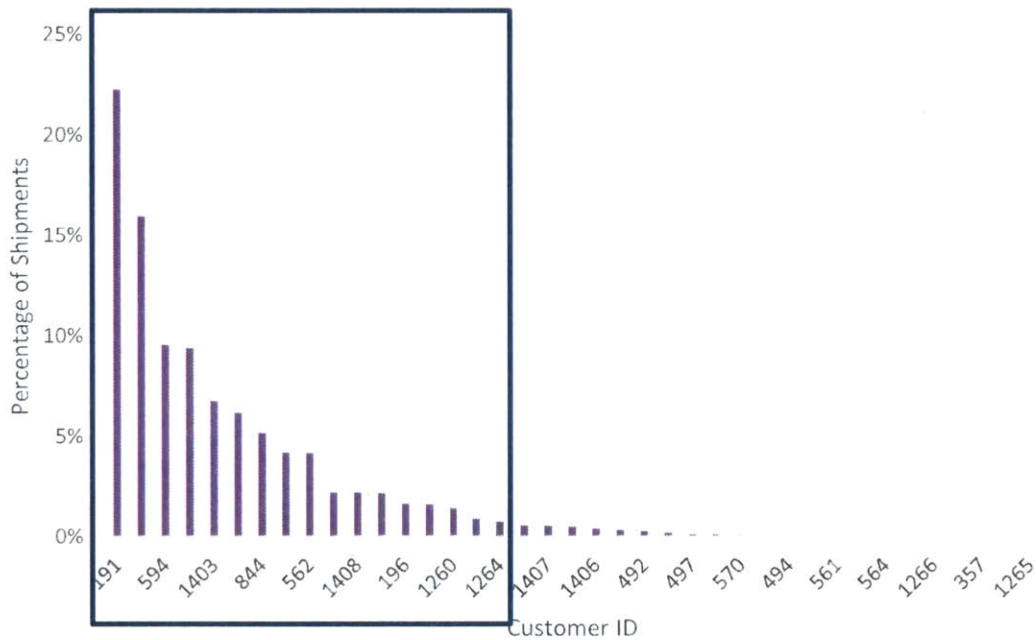

Figure 1: Percentage of shipments by customers

The data-set had the following elements that played a key role in our analysis:

3.1.1. Time elements

Two key time elements were present in the dataset.

- Tendering Date

  The date when the tender was sent to the carrier.

- Shipment Date

  The date when the load ships from the carrier.

We used the tendering date to reference our time-frame. The data-set had 27 months of data from June 2012 to October 2014. Since the number of loads from Jun 2014 to Oct 2014 were limited and were incomplete, the time frame we used for our analysis was 24 months from June 2012 to June 2014.

The average cost per mile variation over the months is mapped in Figure 2. From Figure 2, we can see that the cost per mile has increased linearly over the 3 years. Also, there are peaks in the months of February and March and the months of September and October.

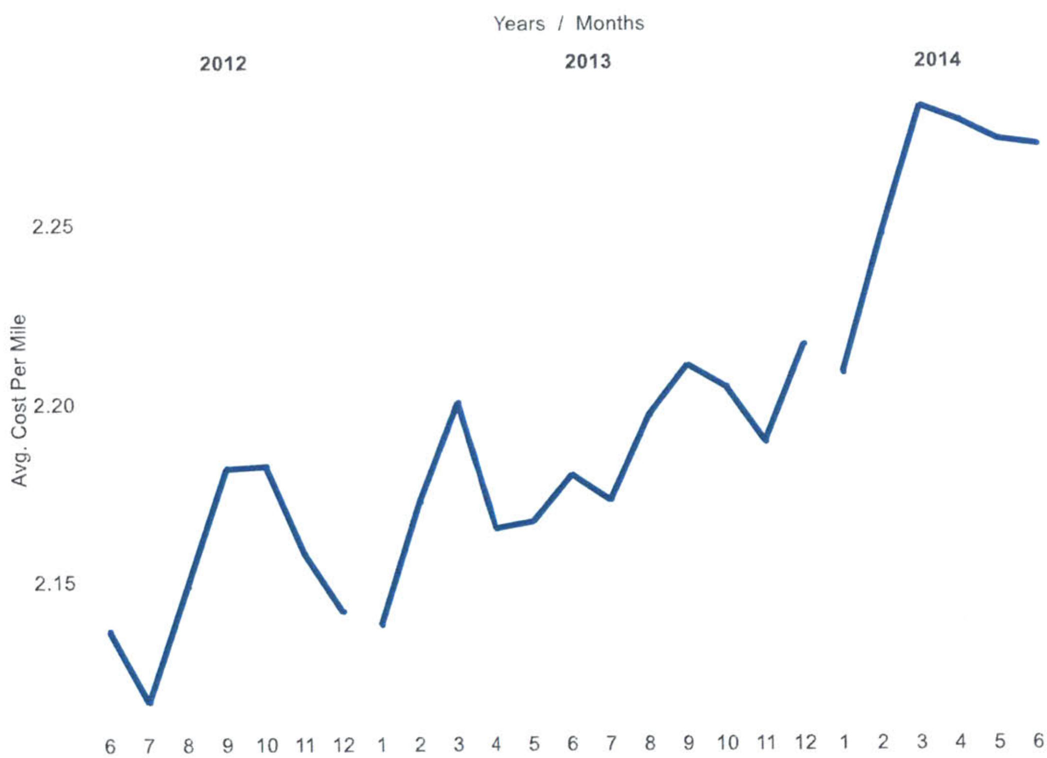

Figure 2: Average Cost per Mile trend over the 24 months

3.1.2. Geographical elements

The transportation network is spread across the mainland United States and Alaska. Some of the key geography variables used in the dataset are as below.

- Origin State

- Destination State

- Origin 5 digit Zip-code

-Destination 5 digit Zip-code

We have used Origin State and Destination State to map the locations in our analysis. However, to test certain hypotheses at a lane level, we have also used the origin and destination lanes defined by 5-digit postal code.

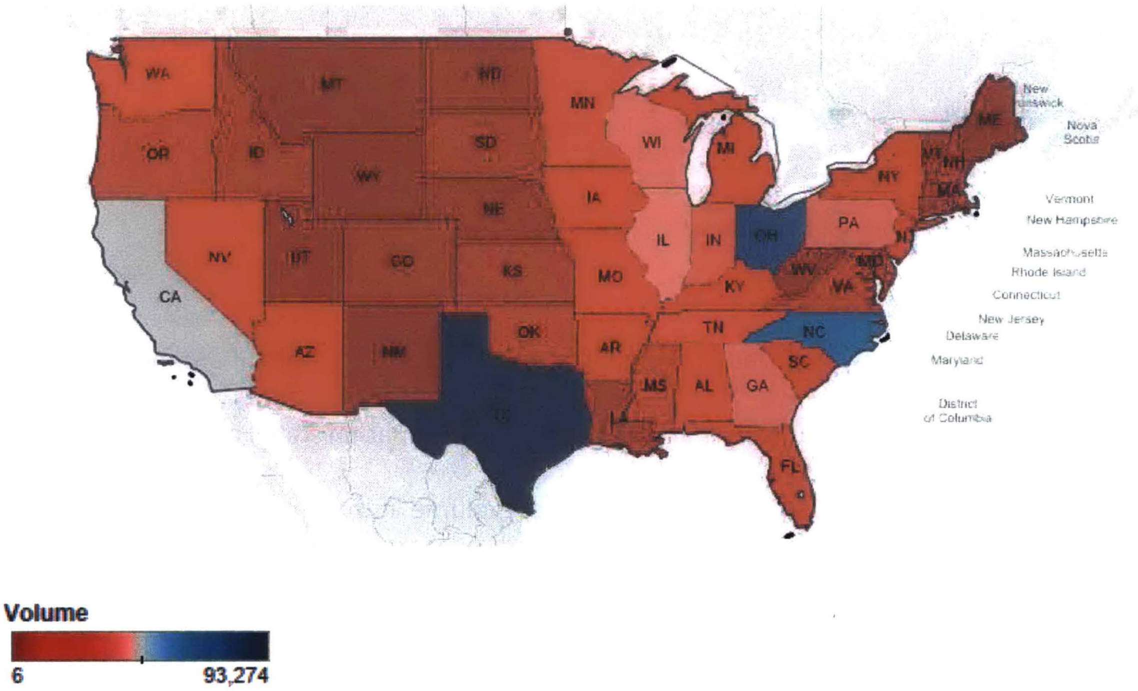

Figure 3: Volume by the origin states

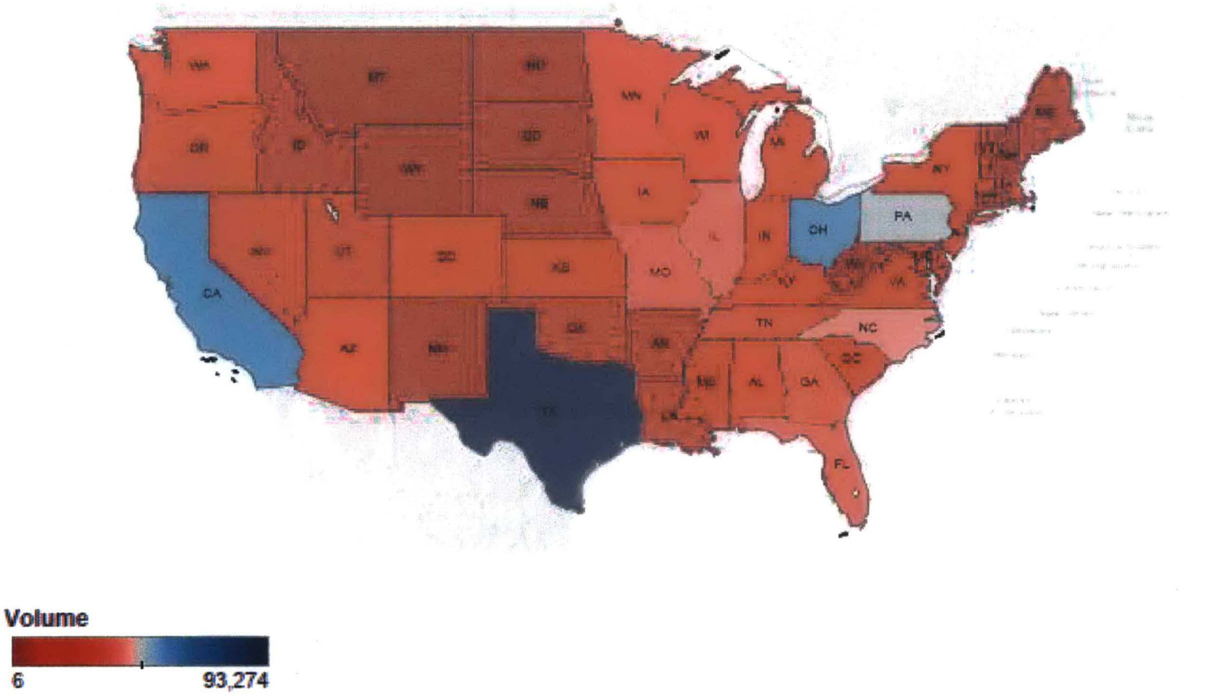

Figure 4: Volume by the destination states

From Fig.3 and Fig.4, we can see that the origin states of Texas, Ohio, North Carolina, California and Illinois have the highest volume in that order. Also, the destination states of Texas, California, Ohio, Pennsylvania and North Carolina have the highest volume in that order.

3.1.3. Cost Element: Total Rate

The cost element present in the dataset is the total rate charged by a carrier for a particular load/shipment offered by a shipper. This element includes line haul, fuel surcharge and other accessorial costs and is charged on a per load basis. It is the key dependent variable in our regression analysis. The shippers' total expenditure in 2013 was $633 Million. Even though the transportation network is spread out throughout the country, it accounted for only 0.23% of the total TL market revenue in 2013 ($280 billion, S&P 2013). The average cost per load in this dataset is about $1500.

3.1.4. Distance (Length of haul)

This data was available in miles and was an independent variable in our analysis. For our analysis, we have only considered length of haul between 250 miles and 3000 miles. The carriers hauled an average of 775 miles. 52% of the loads were for hauls between 250 miles and 500 miles whereas only 16% of the loads were for length of hauls greater than 1000 miles.

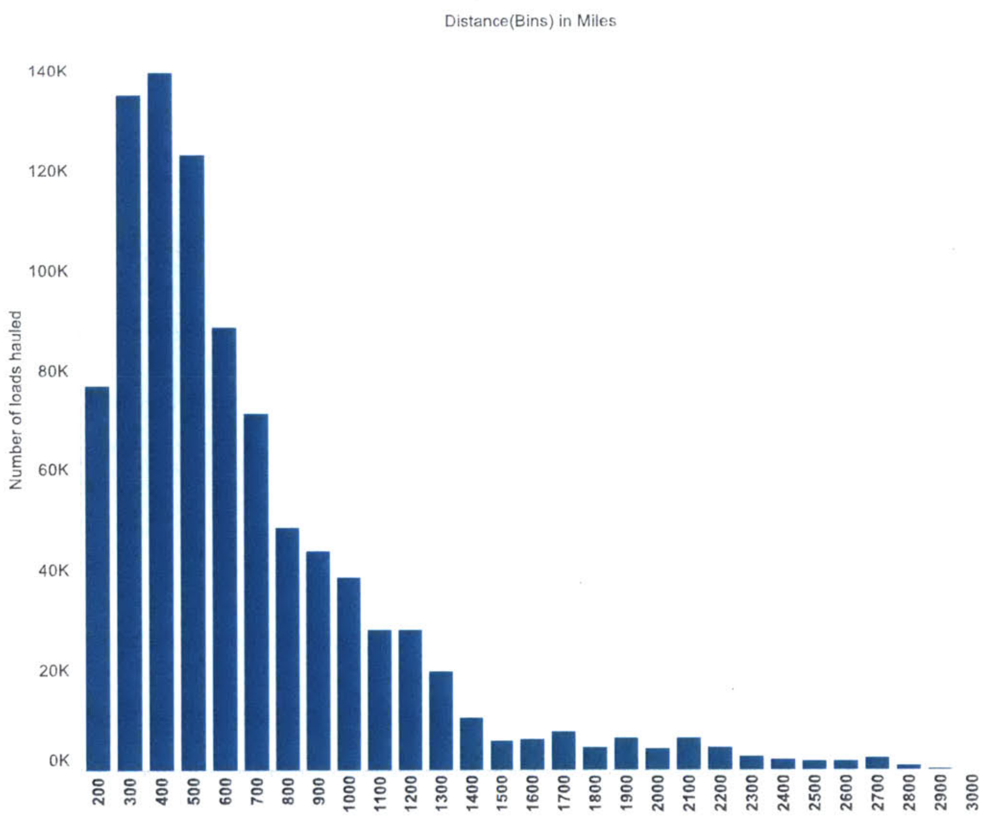

Figure 5: Load Volume by length of haul

3.1.5. Tender Sequence

A shipper maintains a routing guide where he lists the carriers and the price at which they have been contracted. During the tendering process, a shipper refers to his routing guide to award loads to the carriers. The carriers high in the routing guide (with tender sequence of 0 and 1) are the primary carriers. Primary carriers in the routing guide have the lowest tender sequence starting from zero and are preferred by the shippers. As the carriers reject loads from the shippers, the shippers have to dig deeper in the routing guide and look for carriers with higher tender sequence.

3.1.6. Performance Metrics

We will be considering 3 key performance metrics for our research. We will be testing the dynamics of performance with respect to rates offered by the carriers. Also, we will be testing these metrics to see if they have any relationship amongst themselves and their relative importance to the shipper.

3.1.6.1. On-Time Pick-up (OTP)

This is a binary variable in the dataset indicating whether the load was picked up on time by the carrier against a defined time by the shipper either in a formal or an informal contract. Most shippers view this as an important deliverable as they do not want the loads waiting too long and occupying space in their docks. For the analysis, we have aggregated OTP over a period of time and developed a parameter called On Time Pick-up Percent (OTPPercent). While OTP is a binary variable for every load which tells us whether a particular load was picked up on time, OTPPercent explains the OTP performance over a period of time for a particular carrier-shipper combination.

$$OTPPercent = \frac{\textit{Number of accepted loads picked up on time denoted by OTP}}{\textit{Total Number of accepted loads}}$$

Figure 6 shows the number of carriers in different buckets of OTP performance and their average tender sequence. The tender sequence is specified in a shipper's routing guide and is the sequence with which a shipper usually approaches a carrier. From the average tender sequence, we will know if most of the carriers were primary or secondary carriers. We can see that 52% of the carriers had an OTPPercent of greater than 80%, aggregated over 24 months. Also, the carriers with OTPPercent greater than 80% have an average tender sequence of 0.5. This means carrier higher in the routing guide usually perform better when it comes to pick-up.

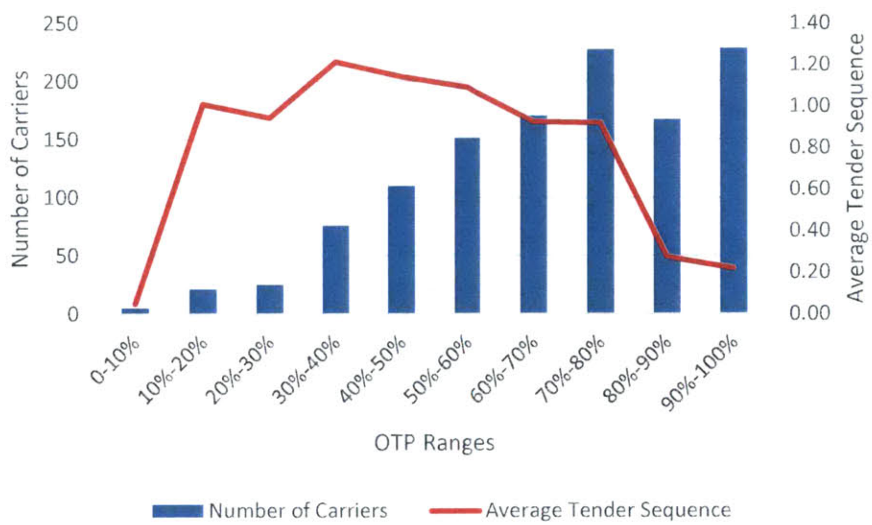

Figure 6: Number of carriers and their average tender sequence in different ranges of OTP

3.1.6.2. On Time Delivery (OTD)

This is a binary variable in the dataset indicating if the load was delivered on time by the carrier to the correct destination against a defined time window by the shipper either in a formal or an informal contract. This is an important performance parameter to most shippers as delayed shipments can result in problems in the shippers' or their customers' supply chain. We begin the research with the assumption that most shippers consider this as one of the measures to rate a carrier. Like OTP, OTD is a binary variable indicating whether a particular load was delivered in time to the shipper or his customer. However, for the analysis, we will use a variable called On Time Delivery Percent (OTDPercent) which explains the OTD performance for a particular carrier over a period of time.

$$OTDPercent = \frac{Number\ of\ accepted\ loads\ delivered\ \ on\ time\ denoted\ by\ OTD}{Total\ Number\ of\ accepted\ loads}$$

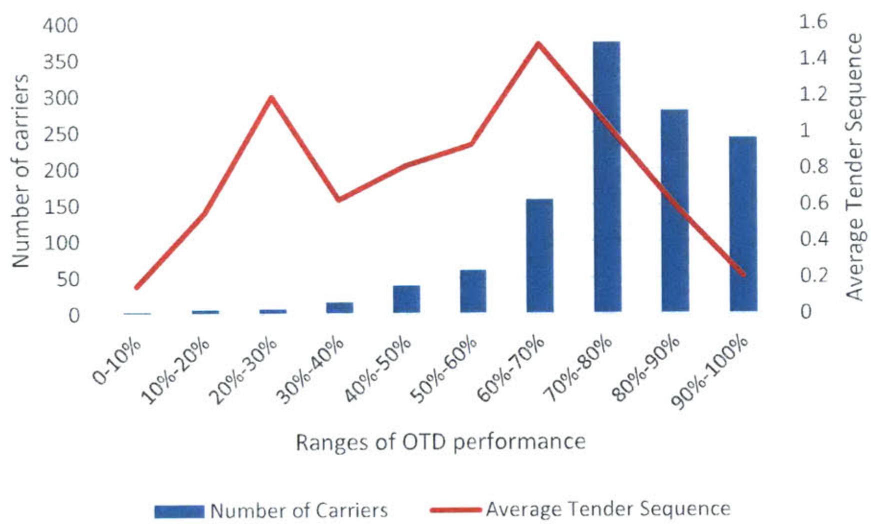

Figure 7: Number of carriers and their average tender sequence in different ranges of OTD

In figure 7, we depict the number of carriers performing in the different ranges of OTD performance and the average tender sequence of all the carriers falling in the different ranges of performance. It is interesting to note that 75% of the carriers have OTD performance greater than 80%, which means that 75% of the carriers have been able to deliver the loads in a timely manner

80% of times. However, the average tender sequence for these carriers is now higher at 0.8.

3.1.6.3. Acceptance Ratio (AR)

Acceptance Ratio is used to decipher how loyal a primary carrier is towards a shipper or how many times a primary carrier has accepted a load offered by a shipper. It is calculated as

$$\boldsymbol{Acceptance\ Ratio = \frac{Number\ of\ accepted\ loads}{Total\ Number\ of\ loads\ offered\ to\ a\ primary\ carrier}}$$

Acceptance Ratio is only defined for a carrier-shipper combination over a period of time. We have used acceptance ratio over a quarter for our analysis. It is expected that carriers high in the routing guide should have higher acceptance ratios and lower prices.

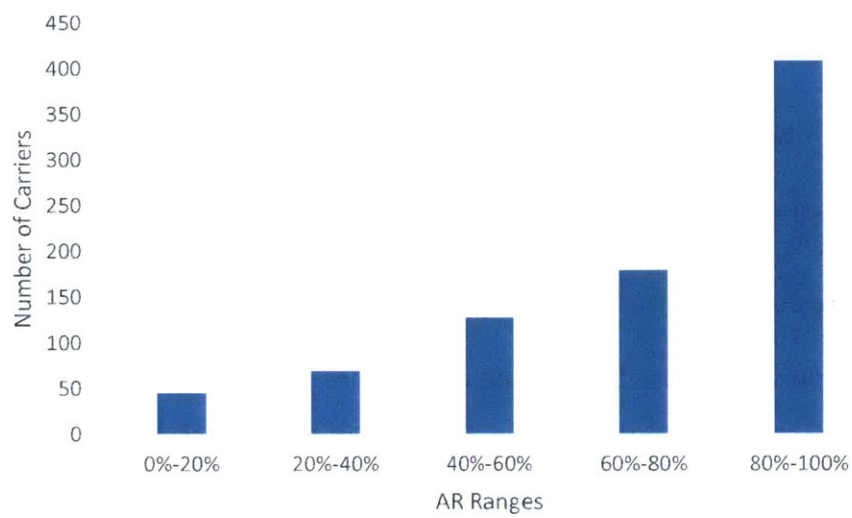

Figure 8: Average acceptance ratios by carriers

About 50% of the carriers have accepted more than 80% of the loads offered to them. The weighted average acceptance ratio for the entire dataset is 73%.

4. Data Analysis

This chapter explains the analytical procedures used to study the data and derive results. Our analysis showed that there is a mild relationship between price and performance.

4.1. Ordinary Least Square Regression

Linear regression is used to find correlation between one variable called the dependent variable with another or a set of other variables called independent variables. Ordinary least square regression tries to minimize the square of the differences between the actual values and the values predicted by the linear regression model for the dependent variable.

The linear regression can be shown as

$$\mathbf{Y=\beta_0 +\beta_1*x_1+ \beta_2*x_2+...+ \beta_k*x_k + e}$$

where x_1, x_2... x_k are the multiple independent variables and the error term, e, is assumed to be a normally distributed random variable with mean $\mu=0$ and standard deviation σ.

We use adjusted R^2 to determine the explanatory power of the regression model. R^2 is the coefficient of determination which will be 0 when the model does not explain the dependent variable at all and will be 1 when there is a perfect fit between the predicted values and the actual values. (Bertsimas, D. & Freund, R. 2004)

4.2. Building the base model

We performed the regression analysis with cost per load including the fuel surcharge and all other costs as the dependent variable. We have used multiple independent variables to draw conclusion for the research. Over the course of our research, we have analyzed more than 120 independent variables. Before we analyze the impact of performance on the total rates, we will study the influence of distance and geography on the cost per load.

4.2.1. Effect of distance

We performed OLS regression with cost per load as the dependent variable and distance as the independent variable. The analysis produced the following model:

Total Rate = 242.2 + 1.78 * Distance

The adjusted R-squared value for this model is 81% which means that the model explains 81% of the variability in the data with just distance as an independent variable. The cost per mile derived from this model is $ 1.78 per mile, while the fixed cost estimated here is $242 per load. Both the coefficients estimated by the model were deemed significant.

To understand what variables further explain the rates, we add in the binary variables for the origin and the destination states.

4.2.2 Adding the effect of geography

To add the effect of geography, we used origin and destination state for the next model. We did not pursue lane level granularity at this point. We assigned binary variables for every origin and destination state. This resulted in 97 independent variables (48 origin state binaries, 48 destination state binaries and distance). We ran the regression with the independent variables - distance, binary variables for origin and destination states and the dependent variable- cost per load for the aggregate dataset of 807,662 accepted loads.

The adjusted R-squared values increased from 81% in the case of the previous model (with only distance as independent variable) to 89%, which meant that an additional 8% of the variability in data can be explained by the geography of the loads. The cost per mile in this case was still $ 1.78 per mile while the fixed cost was $363. It is important to note that the fixed cost is only important relative to the regional values.

Figure 9 and 10 gives insight into cost of servicing specific source and destination states. States with high positive coefficients are more expensive to service both as sources and as destination. The reasons for a more expensive destination state could be empty miles for a carrier on the back-haul. For example, from Fig 10, we can see that Connecticut, New Hampshire, Montana and Maine are expensive destination states to serve. This could be because of absence of loads originating from those sites resulting in empty miles for the truck on the back-haul. From Fig.9, we can see that those same states are very cheap origin states. This is because carriers would prefer hauling loads from those locations at a lower cost rather than serving empty miles on back-hauls from those locations.

Also, we see that the cost of hauling loads on a lane is different from the cost of backhaul on the same lane. From figure 9 and 10, the difference between the average cost per load of a shipment going from Illinois to Florida and a backhaul on the same lane is $1055. Assuming that the distance travelled in the forward haul and the backhaul is the same, this means that the price of hauling a load from Florida to Illinois is cheaper by approximately $1000 than hauling a load from Illinois to Florida. This could be due to the fact that there are many loads originating out of Illinois, but very few originating out of Florida. Hence, the carriers hauling loads from Illinois to Florida will be willing to charge a much lower rate on the backhaul because they are willing to receive a lower pricing on some freight rather than having empty miles for their trucks.

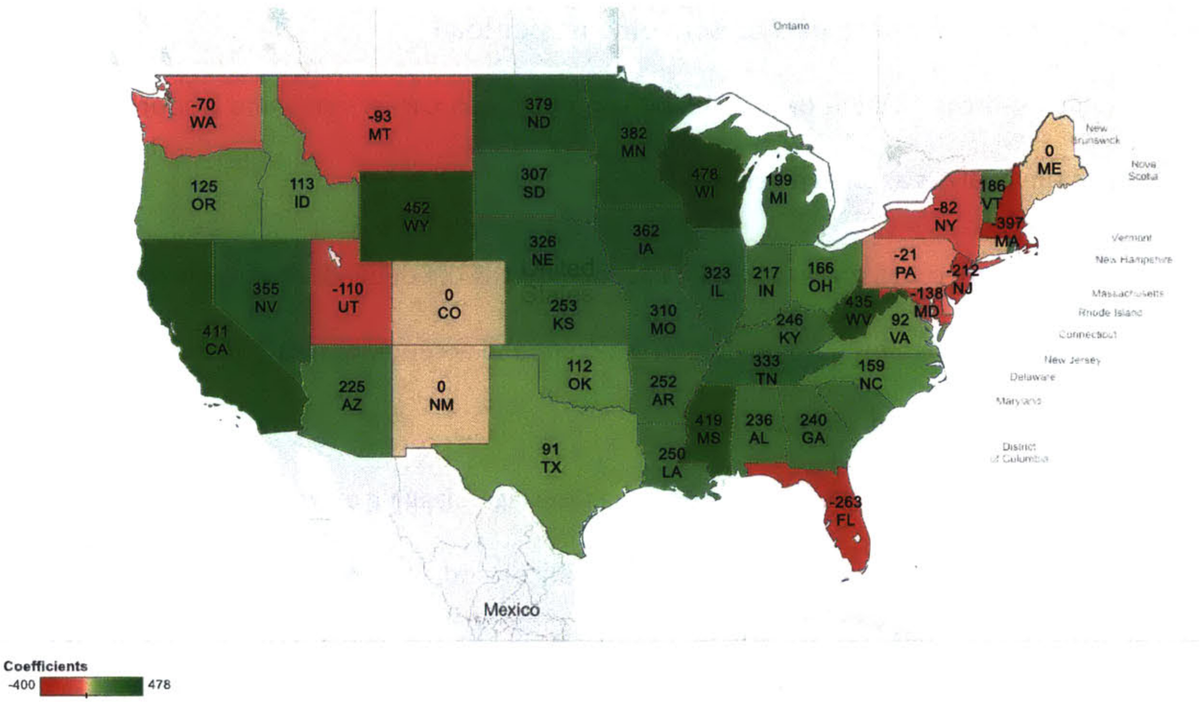

Figure 9: Origin Regional Effects

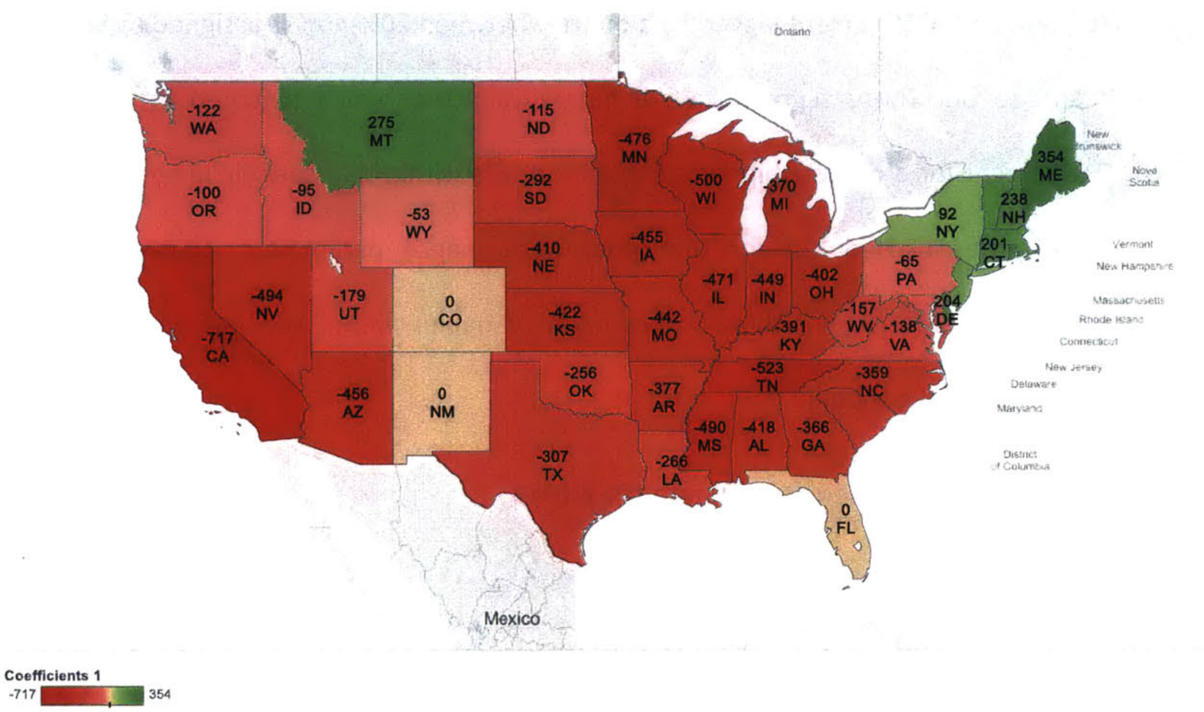

Figure 10: Destination Regional Effects

4.3. Effect of performance parameters on cost per load

To test our research question on the relationship between carrier rates and performance, we performed the analysis as shown below.

1. We performed OLS regression with cost per load as the dependent variable and distance, geography variables, OTPPercent, OTDPercent and acceptance ratio for the same quarter as the independent variable.
2. We then performed the regressions using time lags – lagging one quarter (e.g., Q3 '13 cost per load is correlated to Q2'13 performance) and then lagging two quarters. The performance metrics were tested collectively and independently.
3. For the next model, we assigned binary variables to segments of performance lagged by one quarter. For example, OTDPercent lagged by one quarter between 0-20% is assigned as Segment1, OTDPercent lagged by a quarter between 20%-40% is assigned as Segment 2 and so on. These segments were binary variables, which switched on when the OTDPercent for a carrier-shipper combination falls within that specific range. The same process was carried out for the other performance parameters: OTPPercent and acceptance ratio. Again, these independent variables were used independently and collectively in the model.

A summary of the models used are illustrated in Table 1.

Table 1: Summary of the regression models

Model	Dependent variable	Independent variable	Adjusted R-squared
1	Total Rate	Distance	81%
2	Total Rate	Distance, Geographical binaries	89%
3	Total Rate	Distance, Geographical binaries, OTPPercent, OTDPercent, Acceptance Ratio	89.5%
4	Total Rate	Distance, Geographical binaries, Performance(OTPPercent, OTDPercent, Acceptance Ratio) lagged by 1 quarter	89.5%
5	Total Rate	Distance, Geographical binaries, Performance(OTPPercent, OTDPercent, Acceptance Ratio) lagged by 2 quarters	89.5%
6	Total Rate	Distance, Geographical binaries, Binary segments for OTD lagged by 1 quarter	89.7%
7	Total Rate	Distance, Geographical binaries, Binary segments for AR lagged by 1 quarter	89.6%

For each model, we examined the coefficients and their significance levels for each of the independent variables, especially the ones related to the performance parameters. The adjusted R-squared in case of Model 1 was 81%. On adding the binary variables for the origin and the destination states, the adjusted R-squared increased to 89%, signifying the importance of economies of scope. Models 3-7 however, improved the adjusted R-squared value by less than a percent. We will discuss the effects of individual performance parameters on cost per load.

4.3.1 Effect of On Time Delivery performance on Cost per Load

In our research, time frame used to define a performance parameter (OTDPercent, OTPPercent and AR) is a quarter. We start by assuming that the carrier's current quarter performance results in determining the price being paid to the carrier in the same quarter. However, in reality, rates for a carrier are negotiated before the carrier starts hauling the load in that particular quarter. Hence, we also run other models to see how the carrier's performance lagged by one and two quarters to the current quarter affects its rates in the current quarter.

Table 2: Regression results with performance parameters in current quarter as independent variables

	Cost per load		
Variable	**Coefficient**	**t-statistic**	**p-value**
Intercept	228.10	36.28	<0.01
Geography (Binary, unitless)	476.8,-713	-	-
Distance (miles)	1.79	2254.73	<0.01
OTP current quarter	2.76	1.62	0.11
OTD current quarter	120.71	38.67	<0.01
AR current quarter	26.35	17.53	<0.01

Table 3: Regression results with performance parameters lagged by one quarter as independent variables

	Cost per load		
Variable	**Coefficient**	**t-statistic**	**p-value**
Intercept	238.45	38.51	<0.01
Geography (Binary, unitless)	476.8,-713	-	-
Distance (miles)	1.79	2254.33	<0.01
OTP lagged by 1 quarter	1.18	0.73	0.46
OTD lagged by 1 quarter	93.34	33.90	<0.01
AR lagged by 1 quarter	46.41	28.73	<0.01

Table 4: Regression results with performance parameters lagged by two quarters as independent variables

	Cost per load		
Variable	**Coefficient**	**t-statistic**	**p-value**
Intercept	208.71	33.23	<0.01
Geography (Binary, unitless)	476.8,-713	-	-
Distance (miles)	1.79	2242.17	<0.01
OTP lagged by 2 quarters	7.12	4.90	<0.01
OTD lagged by 2 quarters	117.56	41.64	<0.01
AR lagged by 2 quarters	46.91	28.30	<0.01

In the three models whose results have been shown in Tables 2, 3 and 4, we have used cost per load, including line-haul, fuel surcharge and other accessorial charges as our dependent variable and the distance, geography and the performance parameters as the independent variables. The values of the performance metrics (OTP, OTP lagged 1 quarter, OTP lagged 2 quarters, OTD, OTD lagged 1 quarter , OTD lagged 2 quarters, AR, AR lagged 1 quarter and AR lagged 2 quarters) used in Tables 2,3 and 4 range from 0 to 1. In Table 2, the performance parameters have been considered in the same quarter as the one in which the load was hauled. For example, if the load was hauled in Q1 '14, we use the performance parameters also from Q1 '14. In Table 3, the performance parameters is lagged by a quarter compared to the quarter in which the cost per load is being considered. For example, if the load was hauled in Q1 '14, we use the performance of the carrier in the Q4 '13 as the independent variable. Similarly, in Table 4, the performance parameters is lagged by two quarter compared to the quarter in which the cost per load is considered.

In all the above models, the coefficient of distance is about $1.79 per mile which means for every one mile increase in the distance travelled, the cost per load increases by $1.79. The ranges of output for the binary coefficients for the origin and destination points are mentioned in the tables.

We can see from the output of Tables 2, 3 and 4 that OTD has the largest statistically significant coefficient. It seems that OTD has the most impact on pricing. For the performance considered in the same quarter, we see a statistically significant positive coefficient of 120. This means that for every 10% improvement in the OTD, the carrier charges a premium of $12 from the shipper. The on-time delivery lagged by a quarter has a coefficient of 93 which is slightly lower than the previous coefficient of 120. This again means that based on the previous quarter's on-time delivery performance, the carriers still charge a premium of $9-10 per load for every 10%

improvement in performance. This suggests that there is a correlation between OTD performance and carrier pricing. Carriers seem to charge a premium for good OTD performance.

Also, we observe that the coefficients of the performance parameters lagged by one and two quarters are quite similar. Hence, we will focus our analysis considering one quarter lagged performance parameters. We will use one quarter lag instead of two quarter lag because six months is a longer time frame and will be subjected to higher averaging effects that may result in less differentiation from other carriers. However, practically, shippers remember the performance of the carrier in a more immediate time frame.

We need to explore whether carriers charge a premium uniformly for every 10% improvement in its on-time delivery performance. Do the rates linearly increase with the performance or is there a tipping point beyond which the rates increase more significantly than they did before or do they stabilize beyond this tipping point in performance?

To answer the above questions we divided OTD lagged by one quarter into segments or bins and analyzed the performance in that particular segment. Each segment is a binary variable that will turn on if the OTD performance lagged by one quarter falls in the ranges specified below.

Segment	OTD Performance lagged by one quarter
1	0-40%
2	40%-70%
3	80%-90%
4	90%-100%

Here the segment between 70%-80% is considered as the base segment because, from Figure 7, we can see that the OTD performance of about 35% of the carriers was in the range of 70%-80%.

We conducted OLS regression with distance, geography, and the OTD binary segments as the independent variables and cost per load as the dependent variable. The results are summarized in the Table 5.

Table 5: Regression coefficients for explaining cost per load with OTD segmented by different levels of performance

	Cost per load		
Variable	**Coefficient**	**t-statistic**	**p-value**
Intercept	340.20	59.76	<0.01
Geography (Binary, unitless)	476.8,-713	-	-
Distance (miles)	1.79	2272.23	<0.01
OTD lagged 1 quarter(0-40%)	-51.81	-14.51	<0.01
OTD lagged 1 quarter(40%-70%)	-25.32	-16.62	<0.01
OTD lagged 1 quarter(80%-90%)	21.67	17.27	<0.01
OTD lagged 1 quarter(90%-100%)	23.30	20.37	<0.01

From the results, we can see that if the carrier's OTD performance in the previous quarter has been in the range of 0-40%, which means the carrier has delivered the load on time less than 40% of the times, the carrier is penalized by the shipper. Such a carrier hauls the load for $50 less than a carrier who has delivered on time 70%-80% of the time in the last quarter. Similarly, we can see that a carrier who has delivered on time 40-70% of times in the last quarter has a cost per load of $20 lower than the base case. Also, we see that an OTD performance of greater than 80% allows a carrier to charge a premium of $20 on cost per load. However, this premium does not increase in the ranges between 90%-100%. It remains constant at approximately $20 per load. This means that while carriers are penalized for poor performance, their cost per load does not steadily increase but rather flattens after 80%.

The figure 11 summarizes the output of the regression. We see that below the threshold of 70%-80% OTD performance, carriers charge a lower cost per load than those performing above 80%.

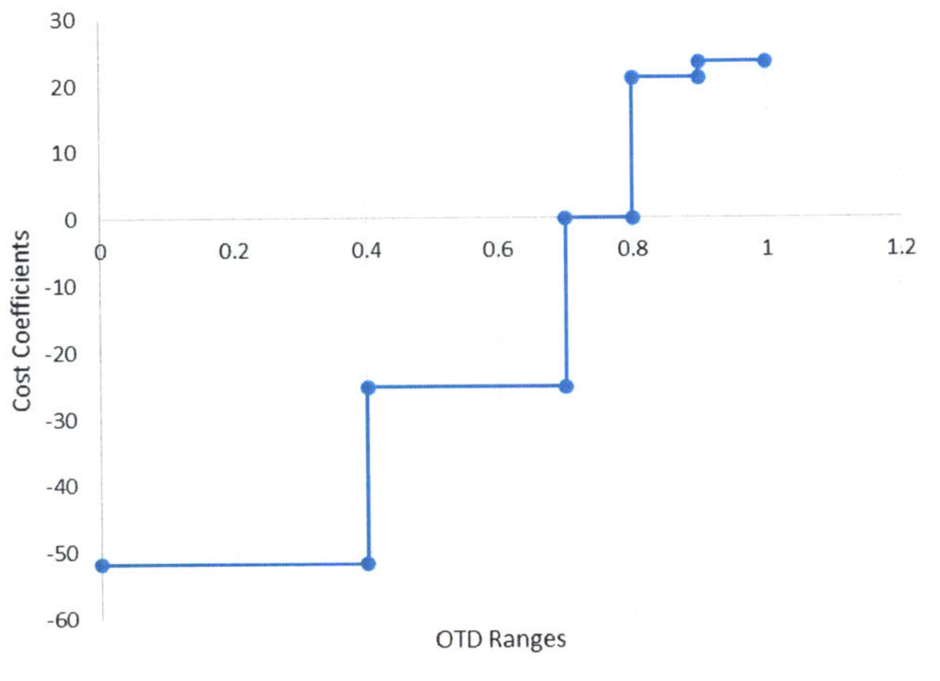

Figure 11: Plot of the cost coefficients for the different OTD ranges as determined by regression

We have been able to establish a relationship between carrier rates and OTD performance. We will next try to see if there is a relationship between carrier rates and OTP performance.

4.3.2. Effect of On Time Pick up performance on cost per load

In the model in Table 2, we see that OTP in the same quarter has a coefficient with a p-value of 0.10, which means that we can reject the null hypothesis that the coefficient of OTP is zero with only 90% confidence. Since the threshold of 5% is chosen as the level of significance, we cannot reject the null hypothesis that the coefficient of OTP is zero. We again observe from Table 3, that the p-value for the coefficient of OTP is 0.46, which means we again cannot reject the null hypothesis that the coefficient of OTP is zero. In case of OTP lagged by 2 quarters, the coefficient of on-time pick up is statistically significant, but still of a much lower order at 7. This means that for every 10% improvement in performance, the cost per load increases by 70 cents. This is still numerically insignificant considering that the average cost per load in the dataset is \$ 1500. From the regression outputs in Tables 2, 3 and 4, it seems that shippers do not really care for on-time pick-up and carriers in turn do not seem to charge for a better on-time pick up.

The regression results of the above models raise several questions. Why is the on-time pick up performance consistently irrelevant in affecting the rates of the carriers? Is there any relationship between the on-time performance and the on-time delivery parameters? Is on-time pick up not as important to the shippers as on-time delivery?

4.4. Relationship between on-time pick up (OTP) and on-time delivery (OTD)

We will first try to find the correlation between the 2 parameters in a shipper-carrier relationship: OTP and OTD. For the same, we first draw a scatter plot of these 2 parameters for all the carriers in the dataset.

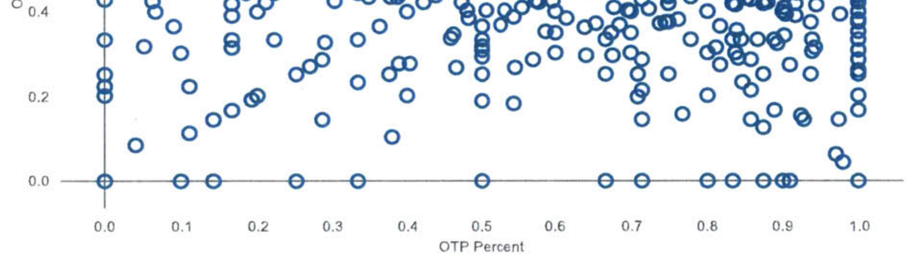

Figure 12: Scatter Plot of OTPPercent and OTDPercent

The correlation between these parameters was significantly low at 18%. To confirm if there is any relationship between these two parameters, we decided to conduct the Chi-squared test.

4.4.1. Chi-squared Test

The Chi- square test is applied on 2 categorical variables drawn from the same population. It is used to test if these 2 variables have an association with each other. The test compares the observed number of cases falling into each category with the expected number of cases that would fall into the categories had there been no association between the two variables. The χ^2 test statistic is as below.

$$\chi^2 = \sum(Observed - Expected)^2 \div Expected\ Value$$

The calculated test statistic is then compared to the values in the table shown in the appendix 3 to find the p-value for the test.

4.4.2. Testing the relationship between On-Time Pick-up and Delivery using Chi-squared Test

The hypothesis we tested are as follows:

Null Hypothesis: OTD and OTP are independent of each other.

Alternative Hypothesis: OTD and OTP have an association with each other.

The total number of loads that were picked up on time is denoted by OTP =1 and the ones that are delivered on time are denoted by OTD = 1. The matrix in table 6 denotes the percentage of loads that were and were not picked up on time and that were and were not delivered on time or not.

Table 6: Matrix with percentages of loads and their OTP and OTD status

All Data	OTP	1	0	Total
OTD	1	62%	25%	87%
	0	7%	6%	13%
Total		69%	31%	100%

We calculated the expected number of loads where (OTP, OTD) = (0, 0), (0, 1), (1, 0) and (1, 1).

The table 7 summarizes the expected and actual values in each of the quadrants of the matrix.

Table 7: Calculated expected and actual values needed to calculate the Chi-squared value

(OTP,OTD)	Expected Value	Actual Value
(1,1)	488235	503977
(0,0)	31061	46803
(0,1)	219172	203430
(1,0)	69194	53452

The above matrix has a degree of freedom (dof) = (2-1)*(2-1) = 1

Using the formula for χ^2 we calculate the value as follows:

$$\chi^2 = \sum(Actual - Expected)^2 \div Expected\ Value$$

$\chi^2 = 13197.1$

The corresponding p-value for the χ^2 statistic of 13197 is less than 0.01. This means that we can reject the null hypothesis with greater than 99.9% confidence, considering 5% significance level for this test. Hence, we reject our null hypothesis that there is no relationship between OTP and OTD.

The same exercise was carried out for 10 of the highest volume customers to validate the results and in each case, it was observed that there is a relationship between OTP and OTD. The outputs of the same are shared in Appendix 2.

Next we tried to find out probability of one influencing the other or predicting one when we know the other. For the aggregate dataset, we found the below probabilities:

Probability of delivering a load on time having picked up the load late is denoted by

P (OTD=1| OTP =0)

Probability of having picked up a load late having delivered a load late is denoted by

P (OTD=0|OTP=0)

Using conditional probabilities as shown below we are able to find P (OTD=1| OTP =0) and

P(OTD=0|OTP=0)

$$\mathrm{P(OTD = 1|OTP = 0)} = \frac{\mathrm{P(OTD = 1 \cap OTP = 0)}}{P(OTP = 0)}$$

From the matrix in table 6, we have the following probabilities

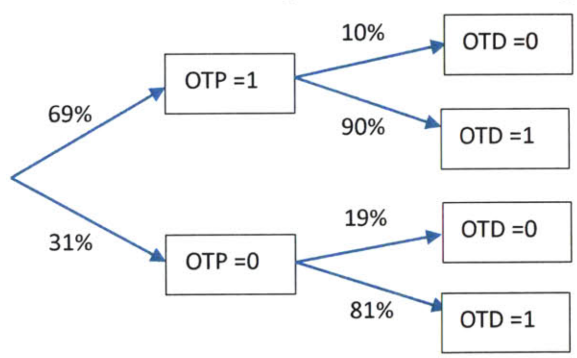

Figure 13: Probability of delivering on time having picked up late

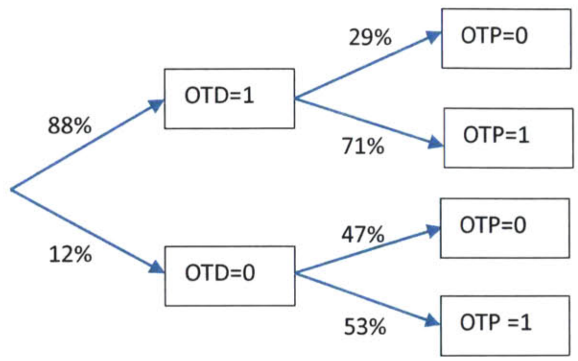

Figure 14: Probability that a load was picked up late having been delivered late

From Figure 13, we can see that there is 80% probability that the carrier will deliver on time even when it has picked up the load late. This may explain why a carrier does not charge a premium for picking up on time or a shipper does not penalize a carrier for not picking up on time. However, we can also see from Figure 14 that of all the loads delivered late, about 50% of them were also picked up late. We have not conducted further research into what kind of a role the late pick-up played in the late delivery or whether there were other factors on the route that prevented these loads from being delivered on time as in the case of the other 80% of the loads that were delivered on time despite being picked up late.

The same analysis was done for the other 10 customers and range observed for the 2 conditional probabilities were as follows:

P (OTD=1| OTP =0) ranged from 63% to 89% with a simple average across the customers of 75%

P (OTD=1| OTP =0) ranged from 30% to 71% with a simple average across the customers of 44%

We can see that most of the late pick-ups also result in on-time delivery. Transit times often have enough extra time to absorb a slightly late departure. Hence, we could not find evidence in the research that the carriers decide their rates based on their on-time pick up performance. It seemed that on-time delivery affected the carrier rates and not on-time pick up.

4.5. Effect of Acceptance Ratio on cost per load

In section 4.3.1, from Tables 2, 3 and 4, we see the coefficients of the tender acceptance is statistically and numerically significant but lower than on-time delivery performance. In the model using performance parameters in the same quarter that the load was hauled, the carriers seem to charge a premium of $2.6 per load for every 10% increase in its acceptance ratio. In the models where performance has been lagged by one and two quarters, the acceptance ratio coefficient at approximately 46 is of a similar order as in the previous model. To dive deeper into understanding whether there are trends in the different segments of acceptance ratios, we have segmented AR lagged by one quarter into four binary variables turn 1 when the acceptance ratios fall within the ranges specified below:

Segment	AR Performance lagged by one quarter
1	0%-30%
2	50%-70%
3	70%-90%
4	90%-100%

AR in the range of 30%-50% is the base case. The regression results are summarized in the Table 8.

Table 8: Regression Results with segmented acceptance ratio lagged by 1 quarter as the independent variable

	Cost per load		
Variable	**Coefficient**	**t-statistic**	**p-value**
Intercept	**382.43**	**66.74**	**<0.01**
Geography (Binary, unitless)	**476.8,-713**	**-**	**-**
Distance (miles)	**1.79**	**2264.00**	**<0.01**
AR lagged 1 quarter(0-30%)	**-26.61**	**-19.78**	**<0.01**
AR lagged 1 quarter(50%-70%)	**-41.75**	**-30.56**	**<0.01**
AR lagged 1 quarter(70%-90%)	**-25.82**	**-27.45**	**<0.01**
AR lagged 1 quarter(90%-100%)	**-1.39**	**-0.83**	**0.40**

From this model, we observe that the coefficients of acceptance ratios (AR) is statistically significant in all the ranges except between 90%-100%. Also, the cost coefficients for ranges from 0 to 30% and 50%-90% is negative. This means that carrier charges a discount in all ranges except for an acceptance ratio of 30%-50% and 90%-100%. While it practically makes sense that a carrier charges a premium for acceptance ratios of greater than 90% from a shipper, it is difficult to understand the motivation of the carrier to charge a premium in the range of 30%-50%. This may be because other factors could be affecting the acceptance ratios and cause it to behave in this manner. Hence, we will look at another factor called shipper loyalty that affects acceptance ratio and try to understand the variable better.

4.6. Effect of shipper loyalty on TL pricing and acceptance ratios

From Table 8 in section 4.5, we did not find a direct relationship between tender acceptance ratios and truckload prices. Hence, we will delve into other factors to see their effect on acceptance ratios and truckload pricing. One of the factors that we are interested in is loyalty from a shipper towards a carrier. We will measure this at a lane level. The hypothesis that we are trying to test is if a shipper is loyal towards a carrier on a few lanes for a period of time, the carrier will build his infrastructure around those lanes and to continue getting loads on those lanes, the carrier will offer lower prices to the shipper. We will be measuring shipper loyalty in 2 ways:

1. Loyalty in terms of number of weeks in a given year the carrier has received a load offer/offers from a particular shipper on a particular lane denoted by Loyalty $_{week}$. This is measured as below:

$$Loyalty_{week} = \frac{Number\ of\ weeks\ a\ carrier\ received\ load\ offers\ from\ shipper}{Total\ number\ of\ weeks\ shipper\ offered\ a\ load\ in\ a\ lane}$$

2. Loyalty in terms of the number of load offer/offers a carrier has received from a particular shipper in a given lane in a year denoted Loyalty $_{vol}$. This is measured as below:

$$Loyalty_{vol} = \frac{Number\ of\ load\ offers\ a\ carrier\ received\ from\ shipper}{Total\ number\ of\ loads\ a\ shipper\ offered\ in\ a\ lane\ in\ a\ year}$$

The number of carriers in different ranges of shipper loyalty across all lanes are shown in Figure 15.

Figure 15: Number of carriers in different ranges of shipper loyalty

We have tested 3 hypotheses with shipper loyalty and truckload pricing.

Hypothesis 1: Shippers showing loyalty to a carrier on a particular lane by offering more loads or consistently offering loads receive lower TL rates from the carrier.

Hypothesis 2: Shippers showing loyalty to a carrier on a particular lane in longer hauls receive lower TL rates from the carrier than on shorter hauls.

Hypothesis 3: Shippers showing loyalty to a carrier on a particular lane have higher acceptance ratios for their loads from those carriers.

4.6.1. Shipper Loyalty and Truckload Pricing

We conducted OLS regression with cost per load as the dependent variable and distance and $\text{Loyalty}_{\text{week}}$ as the independent variables. For this regression, the loyalty was measured at a lane level for a particular year between a carrier and a shipper. The lanes were measured in 5-digit zip codes.

For example, if in a lane, say between 5 digit zip codes 45345 and 28364, a shipper A has offered a load in 50 weeks in 2012, 45 weeks in 2013 and 30 weeks in 2014. Out of those weeks, it has offered Carrier 1 loads in that lane in 30 weeks in 2012, 40 weeks in 2013 and 10 weeks in 2014.

$\text{Loyalty}_{\text{week}}$ for 2012 = 30/50 = 60%

$\text{Loyalty}_{\text{week}}$ for 2013 = 40/45 = 88%

$\text{Loyalty}_{\text{week}}$ for 2014 = 10/30 = 33%

For the regression, we have only included lanes that have had loads more than 10 weeks in a year. The regression results are summarized below in the table.

Table 9: Regression Results Summary for Shipper Loyalty in terms of week and cost per load

	Cost per load		
Variable	**Coefficient**	**t-statistic**	**p-value**
Intercept	377.64	98.52	<0.01
Distance (miles)	1.79	524.79	<0.01
$\text{Loyalty}_{\text{week}}$	-224.94	-30.48	<0.01

From Table 9, we see that the independent variable $\text{Loyalty}_{\text{week}}$ has a statistically significant, numerically large negative coefficient of -224.9. This means that as shipper loyalty increases or as the carrier receives more business in terms of number of weeks in a lane in a year from a shipper, the carrier offers a lower rate or a discount of $22.5 per load for every 10% increase in shipper loyalty. We repeated the study with cost per load as the dependent variable and shipper loyalty in terms of volume ($\text{Loyalty}_{\text{vol}}$) as the independent variable. The results are summarized in Table 10.

Table 10: Regression Summary results for $Loyalty_{vol}$ and cost per load

	Cost per load		
Variable	**Coefficient**	**t-statistic**	**p-value**
Intercept	335.31	77.75	<0.01
Distance (miles)	1.79	519.60	<0.01
$Loyalty_{vol}$	-22.70	-4.51	<0.01

From the above results, we can see the same negative relationship exists between shipper loyalty in terms of volume and cost per load. This means that for every 10% increase in volume, the carrier charges $2.2 lower per load.

However, the usage of shipper loyalty in terms of week is a better indicator than shipper loyalty in terms of volume because different carriers have different capacities and knowing about the carrier's capacity constraint may stop a shipper from offering loads to a carrier. Since, we cannot ascertain the capacity per week of the carriers on a particular lane from the dataset, we will use the loyalty in terms of weeks to focus our analysis.

To see if the lower pricing offered based on loyalty is uniform in all ranges of shipper loyalty, we divided shipper $loyalty_{week}$ into segments or bins and analyzed the performance in that particular segment. Each segment is a binary variable that will turn on if the $Loyalty_{week}$ falls in the ranges specified below.

Segment	Shipper $Loyalty_{week}$
1	20%-40%
2	40%-60%
3	60%-80%
4	80%-100%

The segment between 0-20% is the base case. The output of the regression can be summarized in table 11.

Table 11: Regression results with segments of loyalty$_{week}$ as independent variable and cost per load as dependent variable

	Cost per load		
Variable	**Coefficient**	**t-statistic**	**p-value**
Intercept	367.27	99.48	<0.01
Distance (miles)	1.81	525.1	<0.01
Loyalty$_{week}$(20%-40%)	-82.85	-17.89	<0.01
Loyalty$_{week}$(40%-60%)	-122.56	-17.53	<0.01
Loyalty$_{week}$(60%-80%)	-172.68	-18.33	<0.01
Loyalty$_{week}$(80%-100%)	-165.45	-20.81	<0.01

The output of the regression can also be summarized in figure 16.

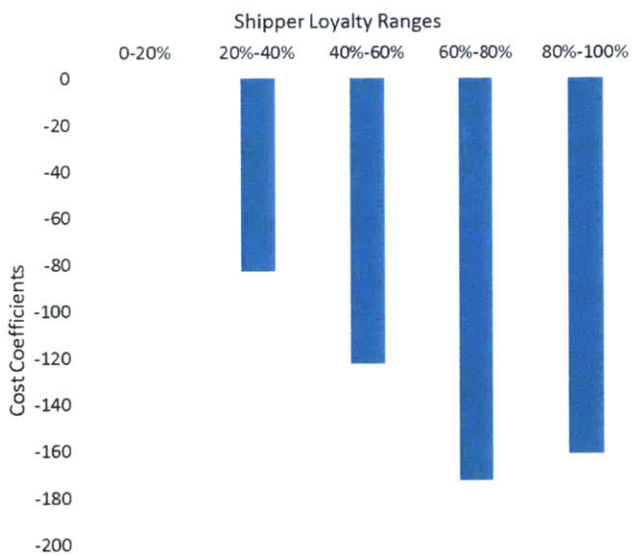

Figure 16: Plot of cost coefficients of different segments of shipper loyalty as determined by the regression

We have seen that shipper loyalty in terms of weeks is correlated with lower pricing. As the loyalty in terms of weeks increases, the cost per load decreases. From Table 11 and Figure 16, we can see that shippers that have loyalty$_{week}$ in the ranges of 0-20% pay about $160-170 more than the shippers that have loyalty$_{week}$ greater than 60%. Also, we can see that the lower pricing based on loyalty flattens out after 60%. This means that beyond 60%, there does not seem to be a correlation with lower prices and higher loyalty. Hence, a shipper may benefit from the lower pricing offered by the carriers by consistently offering a carrier loads on a lane 30 to 35 weeks in a year and may still be able to maintain a couple of carriers who can be used as contingency carriers.

4.6.2. Shipper Loyalty and Truckload Pricing in different lengths of haul

To test Hypothesis 2, we used four variables: $Loyalty_{week}$ (0-500 miles), $Loyalty_{week}$ (500-1000 miles), $Loyalty_{week}$ (1000-1500 miles) and $Loyalty_{week}$ (>1500 miles). The variables are populated as below:

If Distance < 500 miles, $Loyalty_{week}$ (0-500 miles) = $Loyalty_{week}$, else $Loyalty_{week}$ (0-500 miles) = 0

If 500 < = Distance < 1000 miles, $Loyalty_{week}$ (500-1000 miles) = $Loyalty_{week}$, else $Loyalty_{week}$ (500-1000 miles) = 0

If 1000 < =Distance < 1500 miles, $Loyalty_{week}$ (1000-1500 miles) = $Loyalty_{week}$, else $Loyalty_{week}$ (1000-1500 miles) = 0

If Distance >= 1500 miles, $Loyalty_{week}$ (>1500 miles) = $Loyalty_{week}$, else $Loyalty_{week}$ (>1500 miles) = 0

We ran the OLS regression with cost per load as the dependent variable and distance, $Loyalty_{week}$ (0-500 miles), $Loyalty_{week}$ (500-1000 miles), $Loyalty_{week}$ (1000-1500 miles) and $Loyalty_{week}$ (>1500 miles) as the independent variables. The results are summarized in Table 12.

Table 12: Summary of regression for Loyaltyweek in different lengths of hauls and cost per load

	Cost per load		
Variable	**Coefficient**	**t-statistic**	**p-value**
Intercept	332.31	73.56	<0.01
Distance (miles)	1.93	412.34	<0.01
$\text{Loyalty}_{\text{week}}$(0-500 miles)	-278.52	-24.38	<0.01
$\text{Loyalty}_{\text{week}}$(500-1000 miles)	-100.38	-10.22	<0.01
$\text{Loyalty}_{\text{week}}$(1000-1500 miles)	-43.77	-3.17	<0.01
$\text{Loyalty}_{\text{week}}$(> 1500 miles)	-775.01	-39.31	<0.01

From the Table 12, we can see that all the four newly defined independent variables have statistically significant negative coefficients. This reaffirms our previously stated hypothesis that carriers reward shipper loyalty with lower rates. Further, we can see that in hauls greater than 1500 miles, the coefficient of the $\text{Loyalty}_{\text{week}}$ parameter is the most negative and it is least negative in distance between 1000-1500 miles. This means that carriers are more eager to get more loads on shorter hauls (250-500 miles) and on very long hauls (greater than 1500 miles) than on medium hauls (between 500 and 1500 miles). Our hypothesis to explain this finding is that carriers probably align their terminals closely with that of the shippers in the short haul and hence are willing to reward shippers more loyalty for shorter hauls. It may be possible that long haul loads are more profitable and also rarer than medium haul loads. Hence, a carrier encourages shippers offering these loads by giving them a large discount for their loyalty.

4.6.3. Shipper Loyalty and Acceptance Ratio

To test whether shipper loyalty affects the acceptance ratio, we conducted a regression analysis between loyalty in terms of weeks and acceptance ratio. We used acceptance ratio as the dependent variable and $\text{Loyalty}_{\text{week}}$ and a square of the term $\text{Loyalty}_{\text{week}}$ denoted by $\text{Squared\_Loyalty}_{\text{week}}$ as the independent variable. The output of the regression is summarized in the table 13.

Table 13: Regression results for Shipper Loyalty and Acceptance Ratio

	Cost per load		
Variable	Coefficient	t-statistic	p-value
Intercept	0.46	140.4	<0.01
$Loyalty_{week}$	-0.15	-6.7	<0.01
$Squared\_Loyalty_{week}$	0.77	32.1	<0.01

From the Table 13, we see that both the independent variables have statistically significant coefficients. If we plot acceptance ratios using the formula denoted by the coefficients in the above table, we see that acceptance ratio of a carrier for a shipper's load increases exponentially as the loyalty towards the carrier increases in a particular lane.

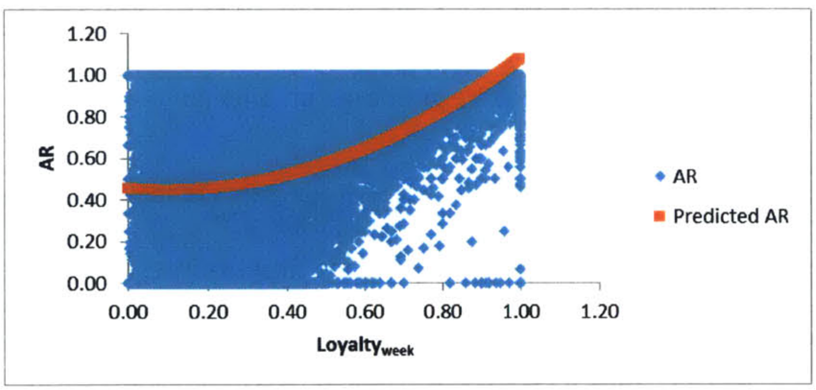

Figure 17: Line Fit Plot of AR w.r.t $Loyalty_{week}$

However, from the line fit plot in Figure 17 and from the adjusted R-squared value of only 10%, we can see that the predictive power of this model is poor. With an intercept of 0.46, the model assumes that the minimum AR a carrier can have on a lane for a shipper is 46%, which is not true. Hence, we have to conclude that there are other forces besides shipper loyalty that determine the acceptance ratios in a shipper-carrier relationship on a lane.

4.7. Chapter Summary

In this chapter, we described how we built and analyzed our transportation cost model. We also presented and discussed the results of the regression models.

Key Research Findings:

Cost per load and OTD performance have a relationship. From our research, we found that carriers are not rewarded for superior OTD performance but are penalized for poorer performance. TL pricing increases as the OTD performance of a carrier increases till a threshold of 80% is reached. However, carriers are not further rewarded for OTD performance above 80%. This insight will help the shippers when negotiating rates with the carrier. Also, it will help the carriers prioritize the level of service and commitment to freight based on pricing.

We also found OTP and OTD have an association with each other. Carriers make up for a delay in on-time pick up more than 80% of the times and deliver on time. Transit times often have enough extra time to absorb a slightly late departure. We could not find a clear relationship between on-time pick up and truckload rates. We concluded that carriers measure themselves on OTD and do not use OTP significantly to decide their pricing.

We could not find any direct relationship between truckload prices and acceptance ratios. Hence, we looked at other parameters like shipper loyalty towards a carrier on a lane and analyzed whether there is a relationship between shipper loyalty and acceptance ratio. When we attempted to find correlation between acceptance ratios and shipper loyalty, we found an obscure relationship between them. It seemed that acceptance ratio increases exponentially as shipper loyalty increases. However, the explanatory power of the model was only 10% and hence, we concluded that along with shipper loyalty, there are several other factors that could possibly contribute to acceptance ratios.

We found that as loyalty from a shipper increases on a particular lane towards a carrier, the carrier starts offering the shipper a discount on the truck rates. This showed that when carriers consistently get loads on a particular lane, they tend to develop infrastructure and plan their networks along those lanes. Hence, they are eager to get more loads on that particular lane and will offer a lower pricing to the shipper to continue sending more loads on that lane. We also found that this lower pricing does not increase significantly beyond 60%. Hence, a shipper has the opportunity to benefit from lower pricing by offering carriers loads consistently on a lane for only 30-35 weeks in a year. We also found that this discount is larger in the shorter hauls (<500 miles) and the longer hauls (>1500 miles).

5. Insights and Conclusion

The purpose of this thesis was to see whether the popular belief in the service industry that higher price commands better performance is true. By using regression models, we have seen that there is some relationship between price and some, but not all, performance metrics. This relationship is more nuanced than a simple positive linear correlation.

We found a correlation between lower OTD performance and lower prices, but not between OTD performance higher than 80% and higher prices. From this, we concluded that the carriers charge lower prices for the shippers for whom their OTD performance has been below 80% but they do not charge a premium on OTD performance above 80%. This implies that shippers penalize poor performance, but do not reward excellent performance.

We could not find a correlation between on-time pick up and carrier prices. We found that 80% of the loads that are picked up late are delivered on time. This seemed to suggest that there was enough buffer in the transit time to make up for this delay. The shippers seemed to care more about the delivery performance than the pick-up performance because the pick-up performance does not significantly affect the delivery performance.

We did not find a correlation between acceptance ratios and carrier pricing on a lane. We concluded that there are other factors that affect a carrier's tender acceptance decisions than pricing. To look at one such factor, we delved into shipper loyalty. We observed that carriers reward shipper loyalty on a lane by offering lower pricing to those shippers who consistently offer carriers loads on a lane. The lower pricing was most prominent in the longer hauls.

5.1. Managerial Insights

Our analysis shows that beyond a certain threshold in performance, higher price does not yield a better performance. This can potentially be used by the carriers to prioritize their commitments and service and by shippers to have clear expectations of performance based on the prices they are paying. The shippers can also use this finding to have differential pricing on different lanes based on service. Also, knowing that price does not guarantee a stellar performance but ensures a steady average performance helps shippers negotiate better rates with the carriers.

At the same time, consistency and loyalty to a carrier on a lane may result in lower rates for the shippers. Our analysis showed that shippers that offer loads to the carriers more than 30-35 weeks in a year receive a lower price of approximately $170 from carriers versus a shipper who only offers loads in a lane to a carrier less than once a month. This pricing benefit is significant as this is more than 10% of the average cost per load on a lane. This can be used by shippers to lower their transportation costs and optimize their transportation network to ensure that they are able to offer loads steadily to certain selected carriers through the year. Also, having the insight that offering loads to a particular carrier on a lane more than 30-35 weeks in a year does not further reduce pricing ensures that a shipper can potentially take advantage of the lower pricing while maintaining contingent carriers in a lane.

Shippers are sometimes tempted to deviate from their routing guides. They wish to use carriers with much lower pricing. We tested the price differential between the most expensive and the least expensive carriers on a lane and we observed that in more than 50% of the lanes, this price differential is less than $170. Hence, it seems that instead of offering loads to multiple carriers based on their spot prices, shippers may gain better long term monetary benefits by offering loads to only a few selected carriers.

5.2. Further Research

When it comes to on-time pick-up and on-time delivery, our dataset had binary variables that just told us whether a load was picked up and delivered on time. It did not tell us about the time-frame within which a load had to be picked up or delivered to be considered "on-time". This time window can be exact to the minute, 15 minute windows, 30 minute, one-hour or even one day windows. It will be interesting to observe how performance in different tolerances or windows affects the total pricing and whether failure to comply to timeliness in a more relaxed time-frame like one-day windows results in a stronger effect on truckload pricing compared to shorter or more restricted windows.

When it comes to acceptance ratio, we were not able to find any steady relationship between performance and price. Also, while we saw that there is an increase in acceptance ratio as the shipper loyalty increases, the explanatory power of the model was very limited. The model seemed to suggest that while shipper loyalty was one of the determinants of acceptance ratio, there were more powerful variables that we had not considered. Research has already been done on several such variables. Kim (2013) showed that volatility of weekly volume on a lane explained tender rejections on a lane to some extent. Another factor that can be considered for future research is the capacity of the carrier to haul loads compared to the general demand for TL carriers on the particular lane in a particular year. Studying high density lanes and how tender acceptance ratios change year on year in these lanes and interviewing trucking companies will further help shippers understand the acceptance patterns of carriers.

Appendix 1:

Adjusted R-squared for the different models

The adjusted R-squared changes only slightly from model 2 to all the other models.

Model	Dependent variable	Independent variable	Adjusted R-squared
1	Total Rate	Distance	81%
2	Total Rate	Distance, Geographical binaries	89%
3	Total Rate	Distance, Geographical binaries, OTPPercent, OTDPercent, Acceptance Ratio	89.50%
4	Total Rate	Distance, Geographical binaries, Performance(OTPPercent, OTDPercent, Acceptance Ratio) lagged by a quarter	89.50%
5	Total Rate	Distance, Geographical binaries, Performance(OTPPercent, OTDPercent, Acceptance Ratio) lagged by 2 quarters	89.50%
6	Total Rate	Distance, Geographical binaries, Binary segments for OTD lagged by 1Q	89.70%
7	Total Rate	Distance, Geographical binaries, Binary segments for AR lagged by 1Q	89.60%
8	Total Rate	Distance, $Loyalty_{week}$	81%
9	Total Rate	Distance, $Loyalty_{vol}$	82%
10	Total Rate	Distance, $Loyalty_{week}$(0-500 miles), Loyaltyweek(500-1000 miles), Loyaltyweek(1000-1500 miles), Loyaltyweek(>1500 miles),	81%
11	Acceptance Ratio	$Loyalty_{week,}$ Squared_Loyaltyweek	11%

Appendix 2:

Chi-squared test performed on individual customers:

Customer: 191

191	OTP	1	0	Total
OTD	1	66293	93767	160060
	0	4538	11382	15920
	Total	70831	105149	175980

		Expected Value	Actual Value
E(OTP,OTD)	**E(1,1)**	64423	66293
	E(0,0)	9512	11382
	E(0,1)	95637	93767
	E(1,0)	6408	4538
	Chi-squared	1003.9	
	p-value	2.58E-217	
	Decision:	Reject	

Customer: 590

590	OTP	1	0	Total
OTD	1	89629	21803	111432
	0	9166	8107	17273
	Total	98795	29910	128705

		Expected Value	Actual Value
E(OTP,OTD)	**E(1,1)**	85536	89629
	E(0,0)	4014	8107
	E(0,1)	25896	21803
	E(1,0)	13259	9166
	Chi-squared	6279.4	
	p-value	0	
	Decision:	Reject	

Customer: 594

594	OTP	1	0	Total
OTD	**1**	52588	6934	59522
	0	12766	5245	18011
	Total	65354	12179	77533

		Expected Value	Actual Value
E(OTP,OTD)	**E(1,1)**	50172	52588
	E(0,0)	2829	5245
	E(0,1)	9350	6934
	E(1,0)	15182	12766
	Chi-squared	3187.8	
	p-value	0	
	Decision:	Reject	

Customer: 594

197	OTP	1	0	Total
OTD	**1**	63807	0	63807
	0	4499	3114	7613
	Total	68306	3114	71420

		Expected Value	Actual Value
E(OTP,OTD)	**E(1,1)**	61025	63807
	E(0,0)	332	3114
	E(0,1)	2782	0
	E(1,0)	7281	4499
	Chi-squared	27289.3	
	p-value	0	
	Decision:	Reject	

Customer: 1403

1403	OTP	1	0	Total
OTD	1	45230	6441	51671
	0	2567	1155	3722
	Total	47797	7596	55393

		Expected Value	Actual Value
E(OTP,OTD)	**E(1,1)**	44585	45230
	E(0,0)	510	1155
	E(0,1)	7086	6441
	E(1,0)	3212	2567

Chi-squared	1011.4
p-value	5.9E-219
Decision:	Reject

Appendix 3:

Chi-square distribution table

D.f.	0.5	0.10	0.05	0.02	0.01	0.001
1	0.455	2.706	3.841	5.412	6.635	10.827
2	1.386	4.605	5.991	7.824	9.210	13.815
3	2.366	6.251	7.815	9.837	11.345	16.268
4	3.357	7.779	9.488	11.668	13.277	18.465
5	4.351	9.236	11.070	13.388	15.086	20.517

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