Data-driven Risk Assessment for Truckload Service Providers

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ABSTRACT

Non-asset backed third-party logistics companies provide shippers access to a flexible source of capacity through transportation carrier spot market. The increased volatility in the trucking spot market rates is turning the 3PL businesses more risky and complex. To maximize profitability, a better understanding of the risk and the volatility patterns across the different geographies, time periods and other factors are investigated based on three years of real spot market data from a major 3PL company in US. Throughout this research we investigate the nature of trucking spot market volatility to allow truckload service providers to reduce their risk when setting long-term contracts. Using three different measures of volatility we are able to assess the company's risk profile and arise with insights to improve truckload service providers' business.

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Sriram Kishore Chittella

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1. INTRODUCTION

The trucking spot market is a marketplace where loads are negotiated on a non-contract basis. The motivation for this thesis originates from limitations for truckload service providers in understanding volatility in the trucking spot market. When referring to truckload service providers, in this research, we mean freight brokers and 3PL (third party logistics) companies. 3PL is an outsourced provider of activities related to logistics and distribution, while a freight broker is fundamentally an entity that connects shippers and carriers. Specifically, we consider them to act as intermediaries between shippers and carriers, as shown in Figure 1.

Figure 1: Third party logistics and broker business

Freight brokers match shippers with carriers for individual loads as well as contracts. Various factors such as changes in economy, weather, carrier capacity, and seasons, can introduce variability in spot market prices. Within this scenario, brokers and

3PL companies need to develop a better understanding of the risk and the volatility patterns of the spot market rates in order to mitigate market uncertainty.

Non-asset based logistics providers or brokers serve shippers that wish to outsource some or all of their transportation needs, by negotiating rates with carriers and manages day-to-day operations for their clients, effectively matching loads with carrier availability and capacity. The difference between the cost of procuring carrier capacity and the rate paid by the customer for the shipment is the margin that these firms earn on the load.

To reduce risk, it is important for brokers and 3PLs to develop an understanding of how the risk and the volatility patterns of the spot market rates are affected by geography, season, and load distance, among others. In this thesis we develop and apply methods for (i) assessing line-haul spot market risk, (ii) identifying factors impacting this risk and (iii) pricing contracts for providing line-haul service on specific lanes. Measures of volatility are defined and applied to key lanes to establish a risk profile. This risk profile is then studied to determine the sources of volatility. Finally, we find the distributions for the spot market prices of various lanes and show how these can used to price the contracts. To initiate the research process, we first considered some important questions:

1) What is volatility?
2) How does volatility impact non-asset does backed 3PL companies?
3) What factors influence spot market volatility?

4) How can non-asset backed 3PL company take advantage of, or mitigate impacts of volatility?
5) How can be volatility and risk be measured and characterized?

The remainder of this thesis is organized as follows. Section 2 provides a background of the trucking industry. Section 3 reviews the literature related to this topic. Section 4 describes the tools, sources of information, and methods we used to collect, treat and analyze the data, as well as describes the scenario presented in the dataset. Section 5 shows the analysis performed through this research and the results obtained. Finally, section 6 summarizes the insights and conclusion from this project, describing the key findings and recommendations.

2. BACKGROUND

2.1. Trucking Industry

In the US, the major transportation mode is trucking. The industry transports about nine billion tons and employed more than 1.3 million people in 2012. With a market valued at $ 681.7 billion in 2013, the trucking business claimed about 81.2% of the US commercial freight transportation market. S&P Capital IQ estimates that aggregate revenues for the US commercial freight transportation market—including the trucking, rail, air, water, and pipeline sectors—reached about $795.6 billion in 2012. As comparison to these numbers, the US air freight was $ 78.8 billion industry in 2012, rail freight $ 39.8 billion industry, water transportation $ 14.4 billion industry, while trucking was $ 642.1 billion in the same year (S&P, 2014). In 2013 the overall transportation sector was responsible for 9.3% of US GDP (US Department of Transportation – Bureau of Transportation Statistics, 2014).

However, despite the sector's size, the trucking industry is a business with low returns on capital, manpower and resources. This requires trucking companies to be more and more efficient if they want to stay in business. In 2013, the seven leading truckload carriers in US average 8.35% in operating margin, ranging from 2.9% to 13.6% (S&P, 2014). Within the trucking industry, freight transportation capacity has been facing pressure from various sources in recent years in US. Many factors have been causing capacity constraints and have been driving rates up. Some of those factors can be predicted, but some cannot.

The trucking industry, involves a wide range of participants, including shippers, carriers, brokers, and 3PLs. Of course there are more actors with different roles involved in this huge industry (e.g. trucking associations, unions, etc.), but for the purpose of our research we consider only the first four entities.

Another important distinction to be made in this market is between private fleets and for-hire trucking segment. The first category relates to companies (shippers) that use their own fleet to move their products, usually when the transportation plays a critical role in achieving the company's goals. A good example of this case is retail stores, which normally operate private fleets to facilitate efficient delivery of products to their stores. In contrast, the for-hire trucking segment is the case when companies outsource their transportation needs, contracting truckload providers to service them with transport. This is the biggest segment of the trucking market, which involves either large motor carriers and own operators, and the one we are going to focus in this research.

2.2. Shippers

Shippers are the central players in the trucking industry. They own the freight and are the decision makers of who is going to move their loads. Shippers are the beneficial owners of freight, and include manufacturers, distributors, and retailers (Sheffi, 2004). They are entities (individual or companies) that have goods to be transported.

As mentioned before, shippers in the US can access truck capacity from either their private fleets or for-hire trucking firms. Although little financial information is available on private carriage, the ATA estimates that companies running their own shipping operations provided services valued at some $292.0 billion in 2012, or about

45.5% of the trucking market, while the for-hire category generated revenues of $350.1 billion in the same year, or about 54.5% of the motor carrier business (S&P, 2014). For example, one of the biggest private fleets in US is owned by Walmart, and they are also a large buyer of for-hire TL services. In today's global economy, when dealing with for-hire trucking, shippers may contract directly with the carriers, may hire third party logistics providers or brokers to procure and manage their freight shipments, or use a mix of both. Even when a company has their own fleet, in most cases, it will still need to outsource a portion (inbound or outbound) of their operation to for-hire carriers or to 3PLs. It is uncommon to find shippers using only private fleets to run the entire business. Walmart, for instance, uses its private fleet in parallel with for-hire trucking firms.

A shipper needs to balance the risks associated from transport of their goods. By making the right decisions and choices, the shipper can dramatically improve the competitiveness of the supply chain and the profitability of the company. The goal of any shipper is to ensure the delivery of the freight to their customer in the right condition, at the right time, at the right price, and in the most efficient way that optimizes the supply chain as a whole.

2.3. Carriers

Freight transportation carriers provide the physical connection between shippers and their customers (Sheffi, 2004). Carriers can be viewed as asset based companies, which own most of the equipment (tractors and trailers) they use to provide transportation services. They usually own or lease the trucks and directly employ the drivers. Sometimes carriers are also called second party logistics (2PLs) from a shipper standpoint. However, large motor carriers can also serve as brokers, as they use owner operators or smaller carriers to move the loads under their responsibility. According to the US Department of Transportation, in 2011, the US total number of interstate motor carriers was 742,762.

We can divide TL carriers in four basic categories: international, national, regional, and independent or owner operators. Independent operators are self-employed commercial truck drivers that own and operate their own trucking business. They may lease to a carrier or they may operate under their own authority.

Regarding the types of equipment, in the US trucking market, carriers can offer a wide variety of trucks, which are differentiated by the type of trailers. The most common types are: Dry Van, Refrigerated, Flatbeds, Liquid Tankers, Containers, Ragtops, and others. There are also some specialized carriers that use specialized trailers as auto carriers, bulk commodity, heavy haulers, cement mixer, dump truck, etc. In other countries the types of trucks can vary from these, depending on culture, infrastructure, regulations, and particular needs that may exist.

However, possibly the most important division of the for-hire trucking industry is the truckload (TL), the less-than-truckload (LTL), and small package delivery (Parcel) segments. Among the largest publicly traded companies in the TL business are companies such as J.B. Hunt Transport Services Inc., Swift Transportation Co., Landstar Systems Inc., and Werner Enterprises Inc. Representing the largest carriers in the LTL business are Con-way Transport, and YRC Worldwide. UPS Freight and FedEx Freight are the largest companies representing Parcel business, even though they do LTL and TL in their operations (S&P, 2014).

As noted by Caplice (2007), truckload transportation firms (carriers) generally handle shipments that are picked up at a location and driven directly to a single destination with no intermediate stops. This is contrasted with less-than-truckload (LTL) or parcel shipments where the individual shipment might be picked up and transported to an initial sorting hub on one vehicle and reloaded onto a separate vehicle for movement to another terminal before finally being loaded onto another vehicle for final delivery (Caplice, 2007).

Truckload (TL) carriers specialize in hauling large shipments for long distances. In this segment, a truck will pick up a load from a shipper and carry it directly to the destination, without transferring the freight from one equipment to another. The TL market is highly fragmented without a single leading actor, mostly due to very low barriers to new entrees. Less than truckload (LTL) carriers usually collect several shipments of smaller sizes from different shippers in one truck that are going to similar locations. The consolidation of freight requires a network of freight terminals. When the shipment arrives at its destination terminal, the load is moved to a pickup-and-delivery truck, and then transported to the final destination. Lastly, parcel carriers usually handle small packages and freight that can be broken down into units less than 150 pounds. For this research, we are analyzing data only from the TL market, limiting it to Dry Van equipment into US territory.

2.4. 3PLs and Brokers

The terms "3PL" and "broker" are often used as interchangeable concepts in the trucking industry. However, in reality, there are some differences between these two terms. Although both entities act as intermediaries between shippers and carriers, their roles can diverge a lot. A broker usually focuses on the execution of an individual shipment, while a third-party logistics provider, in general, works more strategically.

Conceptually, brokers should refer to more basic services and 3PLs to more complex operations.

Another common way to distinguish brokers and 3PLs is from an asset standpoint. At large, brokers are non-asset-based providers, while modern 3PLs might have at least some assets to back their operations. Nevertheless, most of the time, the terms "3PL" and "broker" will overlap, as we can see 3PL companies acting as brokers and vice versa.

We consider only freight brokers in this research. The first freight brokers started in business selling the unused capacity of carriers in a particular region. As the transportation industry developed, brokers began to help shippers to find carriers when they needed transportation, and now it is not uncommon to have freight brokers entering into long-term contracts with shippers to provide transportation on all of a shipper's lanes. After agreed in a contract with the client, the broker then goes to the spot market obtain truck capacity on an on-demand basis to supply transportation for the shipper.

The difference between the price the shipper pays to transport its goods and the price the carrier charge to move the load is the profit the broker makes in this transaction. Since the spot market rates are very volatile and the rates paid by shippers are agreed in advance, the brokers' margin can vary widely, sometimes resulting even in a loss. With that said, we can easily conclude that 3PLs and Brokers profitability derives from their ability to forecast future spot market rates.

The broker's role can be defined as one of a matchmaker between carriers and shippers, helping shippers that need to ship cargo find a trucking company that can deliver the shipment on time and in good condition. The value of a broker is to facilitate a business by bridging an operational or information gap. Brokers and 3PLs provide more flexibility to shippers when the overall truck volume is low and volatile and available trucks are scarce, allowing them to access the trucking spot market without directly participating of it. Brokers maintain relationships with thousands of carriers, and keep track of their performance. Freight Brokers can normally deliver available capacity for the right price.

2.5. Methods of Procurement of Truckload Transportation

Generally procurement is defined as the act of buying, purchasing or obtaining goods or services from a supplier. In terms of truckload procurement, shippers procure transportation using many different approaches. Some of them use a manual approach, usually smaller shippers, while larger shippers are more likely to use systems to manage procurement activities. Most large shippers buy transportation services using requests for proposals (RFPs), leading to contract prices that are typically in effect for one to two years (Sheffi, 2004).

Currently, a wide variety of different electronic market formats can be used for procurement in the truckload industry, including combinatorial auctions, private and public exchanges, and electronic catalogs (Caplice, 2007). The next step after the implementation of one of these tools is to establish the rates for each lane that will be serviced by the carrier for a certain period of time. These rates will be used on the execution stage on a daily basis every time the carrier moves a load for the shipper.

However, besides formal contracts between shipper and carriers, there is also an alternative for shippers to procure truckload transportation, which is accessing the freight spot market. A spot transaction happens usually for a single load and the price is determined by the market only at the time when the load needed to be moved. In the next section we are going to emphasize specifically the trucking spot market, since its understanding is crucial for the comprehension of our research.

2.6. Trucking Spot Market

The trucking spot market is composed of two main players, regular carriers (small and large) and owner operators. Owner operators usually haul as free-lancers, going to the load that fits better their needs. However, in the carrier's case, their role in the spot market is a little bit different. After completion of a load, they need to relocate their equipment to be ready to serve another customer they made commitments to. This makes many carriers willing to sell their extra capacity below market price to return to their original base. Sometimes carriers can lower their service rates down to the marginal cost of service for trips that have to be performed whether or not they carry a load (Garrido, 2007).

The spot market is a common term for single transactions where the price is determined near (or at) the time when the shipper needs extra capacity to move its goods (Bignell, 2013). Due to this logic, the spot market prices can be substantially lower or higher than average market prices, since this market reflects exactly the current transportation capacity and demand.

One method that shippers use is to contract 3PL or freight broker companies in order to access a large number of carriers and to have more flexible capacity. A spot market transaction begins with a negotiation between the shipper and the broker to agree on a rate for a particular lane, followed by the negotiation between the broker and the carriers it has in its network of contacts (Bignell, 2013). When the broker agrees on price with a carrier (or owner operator), the transaction is closed and the load can be moved. The difference between the rate agreed with the shipper and the rate negotiated with the carrier is the margin the broker makes in that particular transaction. Companies such as C.H. Robinson, Total Quality logistics, XPO Logistics, and Coyote Logistics are among the largest brokerage firms in US and North America.

These days, it is very common to have 3PL and broker companies entering the auction process competing with regular carriers, In this case, brokers provide long-term rates for some lanes in order to get annual contracts with the shipper. This is the case of our sponsor (ABC Company), which has many contracts set with shippers, but, as a non-asset based logistics provider, needs to rely in the truck spot market to physically provide the service. Brokerage business logic relies on believing that the aggregate amount that they pay to carriers over the course of the contract will be less than the aggregate revenue received from the shipper. Their success depends on the capability to guess future spot market rates.

For the reasons stated above and many other factors that constrain trucking capacity, the trucking spot market rates are far more volatile than contract rates. According to the DAT Truckload Report (2014), spot market rates exceeded contract rates on 45% of hauls from mid-April to mid-May in 2014. In previous years, between 20% and 25% of spot market rates were higher than contract rates (Thornton, 2014). As we mentioned, this scenario can be influenced by many factors. Regions of origin and destination, types of loads, likelihood of backhaul, total distance and deadhead distance, load and unload time, load weight, and others are always a concern for carriers and owner operators when choosing which load to accept. Likewise, the type of trailer required and specific requirements for the load are also constraints.

There are also hidden factors that play a role in rates' volatility, which will be identified later when analyzing the data on this paper. The most common are: geographic factors, such as seasonality (Christmas, agricultural harvest, etc.); different types of equipment; general economic indicators (e.g. in growing economies GDP puts a pressure on truck availability); government policy (e.g. truck driver hours-or-service regulation changes); load and unload time; week day; manpower capacity; and others.

3. LITERATURE REVIEW

3.1. Introduction: Opportunity for Improved Profitability

Although no substantial research has been done on this specific topic, some previous work has addressed related topics involving the spot market of the transportation industry. Third-party-logistics (3PL) providers connect shippers with carriers by matching loads with truck capacity. The difference between the cost of procuring truck capacity and the price paid by the shipper for the shipment is the margin the 3PL company earns on a load. The price charged to the shipper is generally agreed upon in advance via an annual contract. In contrast the truck capacity is obtained from the spot market within a week of the scheduled load pickup time.

Bignell (2013) explores the importance of utilizing trucking spot market rate information and knowledge to improve contract formulation and negotiation. Because rates with shippers are established prior to negotiations with carriers, the margin achieved by a broker on any particular transaction can vary widely and may even be negative, depending on general economic conditions, market trends, and seasonal variations.

In addition, Bignell (2013) also establishes that spot market behavior varies geographically and with respect to time. This thesis explores a better understanding of the spot market volatility patterns across the various markets. Very limited research has been conducted thus far in the scientific community to gain an in-depth knowledge of volatility in truckload spot market prices. Such research has been performed for spot electricity market, airline tickets and commodities such as silver and fuel.

By acknowledging this gap in literature, our final objective is to identify and quantify individual patterns of volatility in the spot market, and based on that, to produce a data-driven model that allows freight brokers and 3PL companies to assess and reduce their risk. This knowledge can be utilized to enhance existing contracting models with carriers to reduce risk. Since there is very limited research specific to a truckload spot market on this topic, other types of spot markets are also within scope as the findings from those markets may be closely applicable to the truckload spot market. The literature review focuses on the following topics: price volatility in spot market; factors contributing to price volatility in spot market; volatility patterns with respect to time and location; and mathematical analysis.

3.2. Price Volatility in Spot Market

Price volatility in spot market transactions is a popular topic of study among researchers in the commodities and financial markets. Over the years, researchers have studied the price volatility of a variety of items including financial instruments such as stocks and commodities such as silver, electricity and fuel. In the research conducted by Simonsen on volatility of power markets, volatility is defined as a characteristic to measure the fluctuations or risk associated with purchasing (Simonsen, 2005).

In a separate study conducted by Gillen and Mantin on price volatility in the airline markets, volatility is defined as the level of uncertainty associated with the erratic change of the value of an item over time (Gillen & Mantin, 2009). Simply put, this measure is utilized to answer how well and the degree of certainty with which one can predict the change in the price of an item. Standard deviation of the price is the descriptive statistic that is proposed to be utilized to measure the volatility in that case. Further, it is suggested by Gillen & Martin that volatility indicates the overall instability and deviation of the demand relative to the general expectation for a good or service.

Therefore, volatility of the prices may in reality indicate that the demand itself is volatile. The instability and volatility in prices is seen as a significant factor in customer's future expectations of prices and relevant decisions. In the financial industry, volatility is a measure that is utilized to quantify the risk associated with a financial instrument. A common volatility measure in the financial sector includes the Chicago Board of Options Exchange (CBOE) Volatility Index (VIX) which measures the volatility of the S&P 500 and is known to measure the volatility of the index. Other applications of volatility models suggested by Simonsen include the foreign exchange market as well as the volatility associated with the inflation of an economy (Simonsen, 2005). Exponential smoothing approach is also investigated due to its simplicity. In the case of the electricity model, volatility is seen as an important and useful input into models that forecast the prices in electricity markets. Conceptually the same approach can be applied to the carrier transaction data to improve the contract and the pricing strategy between the shipper and the carrier.

3.3. Factors Contributing to Price Volatility in Spot Market

According to Cassidy, the spot market for truckloads is quite close to the market equilibrium (Cassidy, 2010). Carrier executives believe that the volatility, uncertainty and imbalance is caused as a result of various factors such as shortage of truck drivers, rising and fluctuating fuel costs and increasingly constrained regulatory environment. In the same line of reasoning, Thornton emphasizes that the responsible for higher rates in the trucking market are factors that constrain capacity, including more stringent regulations, extreme weather, increasing operating costs, and a chronic shortage of experienced drivers (Thornton, 2014). As mentioned previously, the freight transportation market has been facing many ups and downs in the last two or three years, causing freight brokerage business to become more risky as this volatility is poorly understood by the main players.

Particularly, the rising fuel prices negatively impact smaller carriers with older trucks who do not have much leverage in negotiating spot market prices and recovering fuel surcharges. On the other hand larger carriers have greater power in price negotiations and are equipped with newer and more fuel efficient trucks. In the case of fuel prices, large and erratic fluctuations may occur due to several different reasons ranging from geopolitical unrest in oil producing nations to refinery capacity constraints and weather disruptions. Furthermore, the government has made efforts to improve the drivers' conditions by proposing to introduce more mandatory breaks, reduce the driving time per day and equip trucks with monitoring and safety devices. As per industry experts these changes can directly increase the cost to the carrier thereby increasing the overall volatility and baseline for the trucking spot market prices. In the case of the research conducted on the airlines industry by Gillen and Mantin, market share i.e. the number of planes is seen as a factor that influences the volatility (Gillen & Mantin, 2009). A dummy variable is introduced in the regression model to indicate whether or not the market share for a single carrier is more than 90%. In addition, other factors that were identified by Gillen and Mantin include the presence of a low cost carrier in the route being taken by the company, the total distance of the lane and whether or not the journey is non-stop.

3.4. Volatility Patterns

Simonsen observes the phenomenon of volatility clustering in spot markets whereby the volatility of prices is intermittent with periods of high volatility followed by less volatile periods. Simonsen further investigates the relationship between volatility and time by examining the temporal volatility-volatility correction function to quantify the concept. In addition, he observes that prices are particularly more volatile in the summer months than rest of the year, thus illustrating the time-dependent nature of volatility (Simonsen, 2005).

Volatility also varies with respect to price levels. At low price levels of spot prices, there is a stronger relationship between volatility and price levels i.e. volatility increases with an increase in price. On the other hand, at high price levels, there is a weak relationship between volatility and price levels. While our research focuses on the spot market price volatility of truckloads, the volatility patterns observed in other markets such as commodities and financial instruments will offer fresh insights and creativity. Similarly, Gillen and Mantin investigate how volatility changes with respect to time in the airlines market. It was done by plotting and studying the change in volatility with respect to time across the different geographies (Gillen & Mantin, 2009). Volatility drastically increases during the last 2 weeks of the month though the average price level may not necessarily increase or decrease, thereby confirming the time dependent nature of volatility.

3.5. Mathematical Analysis

A mathematical technique commonly used in the volatility analysis of the prices in the various spot markets is regression analysis. For example, in the spot market for airline tickets, Gillen and Mantin performed regression analysis to identify the underlying determinants of price volatility (Gillen & Mantin, 2009). In order to do this, market structure variables were formulated to represent the market concentration (Hirschman-Herfindahl Index), market domination and whether or not an airline was low cost. In addition, a distance variable was included to represent the route characteristics. By simulating the regression models with the various explanatory variables and examining the R^2 values generated, Gillen and Martin were able to determine whether or not each of the factors had any influence on the volatility of the prices (Gillen & Mantin, 2009). In the specific example, it was determined that the presence of a low cost carrier on a specific route does not impact the price volatility.

When modeling the volatility of railway freight in China, Dai, Sriboonchitta and Li (2012) used symmetric and asymmetric conditional volatility models (GARCH, GJR-GARCH and EGARCH) in order to estimate the volatility in monthly railway freight volume. According to their results, it indicated that the volatility has an asymmetric effect on risk from positive and negative shocks of equal magnitude.

In addition to the transportation field, we also considered options in different fields with similar behaviors. One option that makes sense for us is the finance market. In finance, the risk of stocks and options is calculated by using the stock prices' volatility. By testing the significance of beta, stock riskiness is predicted (Bahhouth, Maysami and Khoueiri, 2010). To determine an option price risk in units of stock price risk is relevant for hedging, risk management, asset pricing and performance measurement (Branger and Schlag, 2007). This approach is in some way analogous to the 3PL companies acting in the trucking spot market, in which they have to "bet in" a rate while setting contracts with shippers and later they have to buy transportation capacity in the spot market.

3.6. Conclusion: Cross Industry Insights

The trucking industry in US provides an essential service to the US economy by transporting large quantities of raw materials, works in process, and finished goods over the country. In the past three years, 3PL enterprises were struggling to predict future trucking spot rates. In our research, we will try to fill this gap when understanding the volatility that exist in this specific market, making it easier to be explored. We will focus on understanding the spot trucking market behavior to posteriorly create a feasible model able to enhance the spot rates forecasting process. 3PL providers will benefit from a better understanding of rate volatility and able to increase their business' profitability.

It is evident through the literary review that there is very limited knowledge regarding the spot market price volatility in the freight transportation and truckload industry. It is recommended to adopt some techniques and methodologies utilized in other industries and apply them specifically to the truckload spot market price volatility scenario to develop an in-depth understanding of truckload spot market price volatility.

4. METHODOLOGY AND DATASET

In this section, we describe the tools, sources of information, and methods we used to collect, treat and analyze the data. We also will describe the scenario presented in the dataset.

4.1. The Dataset

The original data were provided by our sponsor company's strategic team, which were extracted from the company's system. The dataset includes shipment records of dry van equipment, nationwide (US) over the past three years (From October 2011 through September 2014). The data are composed of 1,609,594 rows of load shipments during this three years period. Each row of data indicates a load shipment by a carrier to a shipper and consists of the attributes shown in table 1.

Table 1: *Data attributes*

Attribute	Description
LoadID	The identification number of the particular load
Ocity	The origin city of the load
OST	The origin state of the load
Dcity	The destination city of the load
DST	The destination state of the load
OriginLatitude	The latitude of the load origin point
OriginLongitude	The longitude of the load origin point
DestinationLatitude	The latitude of the load destination point
DestinationLongitude	The longitude of the load destination post
OZIP	The origin zip code of the load
DZIP	The destination zip code of the load
LoadDate	The date when the load is picked up
Miles	The total distance traveled by the load between points of origin and destination
Weight	The weight of the load
TotalCost	The total cost of the load, paid to the carrier including fuel cost
Year	The year in which the load is shipped
Week	The week in which the load is shipped
Pickup	The time and date when the load is picked up from origin
Delivery	The time and date when the load is delivered to destination

The origin and destination are described by providing City, State, Latitude and Longitude, and the total cost provided in the raw data includes the cost of the fuel.

4.2. Data Preparation

In this section, we will review how we cleaned, normalized, and grouped the dataset provided to better fit our research needs.

4.2.1. Data Cleaning

We decided to filter out some outlier shipments using the criteria in Table 2.

Table 2: Data cleaning

Data cleaning operation	Rows removed
Remove records that consist of distances which are 0 or less	5448
Remove records that consist of cost per load (total cost – fuel cost) which is 0 or less	8954
Remove records where OZIP is "NULL" Or Is Null	1322
Remove records where DZIP is "NULL" Or Is Null	3777

Thus the data set condensed from 1,609,594 transactions to 1,590,093 transactions after data cleaning, or 98.79% of the original data.

4.2.2. Data Normalization

To be able to compare lanes with different distances, we normalized the shipment costs by transforming the total cost per shipment into a per mile basis.

The fuel cost was isolated from the linehaul cost to avoid any fuel related cost fluctuations. We estimated the fuel cost using the Department of Energy On-Highway Diesel Fuel Price Index. We converted the $/gallon to $/miles based on average fuel consumption, which was currently (as of the most recent published number) $0.46 per mile for the US average, using the index published by PADD. With this information, we were able to derive the historical weekly prices using published data.

4.2.3. Data Aggregation and Selection

We aggregated and selected the data for analysis purposes. On top of the segmentation we decided to aggregate the data in terms of lanes origin and lanes destination. The data was aggregated in lanes by 3 digit origin and destination zip codes to improve significance and relevance. This resulted in an aggregated data set consisting of 1,164,953 spot transactions.

Each transaction consists of Load Date, Origin and Destination State and 3-digit ZIP, Cost per load without fuel (Average, Minimum and Maximum), Distance (Average, Minimum and Maximum), Cost per mile and Load Count. Load count indicated the number of loads in a particular 3-digit to 3-digit lane. The average, minimum and maximum costs and distances are calculated using the information for a 3-digit to 3-digit lane for a particular day.

The data set was then further transformed to categorize the loads by region based on the state of origin. This was done by grouping each of the states into 5 categories: West Coast, Rocky Mountain, Midwest, East Coast and Gulf Coast. East Coast is divided into New England, Central Atlantic and Lower Atlantic Regions. District of Columbia is grouped under the Central Atlantic region. This is based on the Department of Energy Petroleum Administration for Defense Districts map as shown in Figure 2.

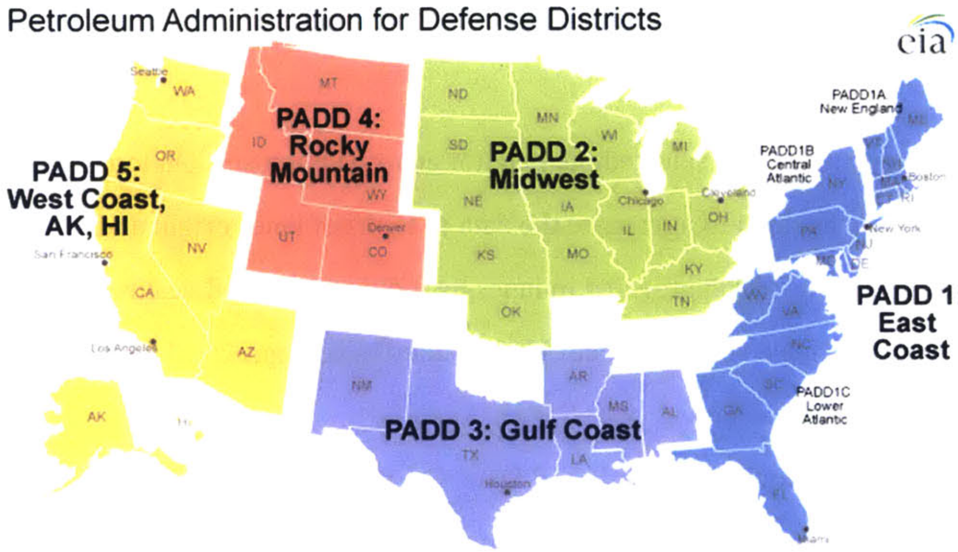

Figure 2: Petroleum administration for defense districts map

4.3. Measures of Volatility

Three measures of volatility were utilized to quantify the volatility and to characterize the risk: Coefficient of variation (CV), beta (β) and average month/month percentage change (AMoM).

4.3.1. Coefficient of variation

The coefficient of variation (CV) is a standardized measure of dispersion of a frequency distribution. It is defined as the ratio of the standard deviation to the mean. The coefficient of variation is useful because the standard deviation of data must always be understood in the context of the mean of the data. In contrast, the actual value of the CV is independent of the unit in which the measurement has been taken, so it is a dimensionless number. CV is calculated as:

$$CV = \frac{\sigma}{\mu} \tag{1}$$

Here σ is the standard deviation of the linehaul cost per mile and μ is the average of the linehaul cost per mile. The CV is calculated based on the monthly values of σ and μ during 2012 and 2013.

4.3.2. Beta

The Beta value is utilized to indicate the relative risk of a lane in comparison to an index such as the national index or the CASS index. Beta is calculated as:

$$\beta = \frac{Cov(x, y)}{Var(y)} \tag{2}$$

Here x is the cost per mile values of a lane and y is the cost per mile values of an index within a time period. To calculate a β value for a time period, the average monthly values are utilized within the time period. The values for the beta for a given region or lane can be interpreted as described in the Table 3 below. The time intervals used for the beta calculations can be quarter to quarter or yearly.

Table 3: Beta value interpretation

Beta Value	Interpretation
β<0	Regional index moves in the opposite direction as compared to the national index
β=0	Regional index is uncorrelated to the national index
0<β<1	Regional index moves in the same direction as the national index but is less volatile
β=1	Regional index moves in the same direction as the national index and by the same amount
β>1	Regional index moves in the same direction as the national index and is more volatile

The reliability of the beta values is calculated using Pearson's product-moment correlation coefficient (R-Squared value). This measures the linear correlation (dependence) between two variables giving a value between +1 and -1. 1 indicates total positive correlation, 0 indicates no correlation and -1 indicates total negative correlation.

4.3.3. Average month/month percentage change

As the third measure, volatility is calculated by examining the average month over month percentage change in the cost per mile rates based on the average monthly rates for each region. This indicates the extent to which the cost per mile rate varies on a monthly basis. It is calculated as:

$$Avg = \frac{\sum_0^n \left[\left(\frac{M_n}{M_{n-1}}\right) * 100\%\right]}{n} \tag{3}$$

Here M_n indicates the average monthly cost per mile rate for month n and M_{n-1} indicates the average monthly cost per mile rate for month $n-1$.

4.4. Lane Characterization

A subset of data of 3digit-3digit zip code, which have at least 1 load per month every month for 2012 and 2013 are utilized to more closely analyze and understand the characteristics of individual lanes. In total when aggregating the data by month, there are 90,275 unique 3digit origin to 3digit destination zip code lanes. Once this data is filtered out to include only lanes which have at least 1 load per month every month for 2012 and 2013, the number of lanes is reduced to 674. If the zip code 3 digit zip code lanes are filtered out to include only lanes which have at least 1 load per week every week for 2012 and 2013, the number of lanes is reduced to 30. On average, the national linehaul cost per mile changes by 0.41% week over week during 2012 and 2013 and 1.51% month over month. The coefficient of variation are 0.08 and 0.09 monthly and weekly respectively. Hence monthly values were utilized to ensure a sufficiently large data set across the various regions. However, weekly analysis is conducted on the Laredo to Houston (780-770) lane in the Management Implementation section of the thesis. The lanes are then characterized by volatility and risk based on the Beta value for 2012 and 2013 against the national index as well as the coefficient of variation and average monthly percentage change for 2012 and 2013.

4.5. Factors Related to Volatility

The relationships between volatility, distance and volume are investigated. Volatility is examined using both beta and the coefficient of variation. First, the relationship between coefficient of variation and beta is examined to ensure that both the measures are relevant.

4.6. Linear Regression

Using the monthly average cost per mile in years 2012 and 2013 for each region (Central Atlantic, Lower Atlantic, New England, Gulf Coast, West Coast, Mid-West, and Rocky Mountain) as the dependent variable, and interchanging some independent variables, such as GDP Index, date (month and year), number of trucks at origin, and commodities seasons (agricultural activity), several regression analysis were performed to test which factors influence or do not influence the spot market rates in a given region.

Figure 3 shows the commodity map used to account for the crops' seasons by regions, which was provided and developed by our thesis sponsor (ABC Company), based on their empirical analysis over the years.

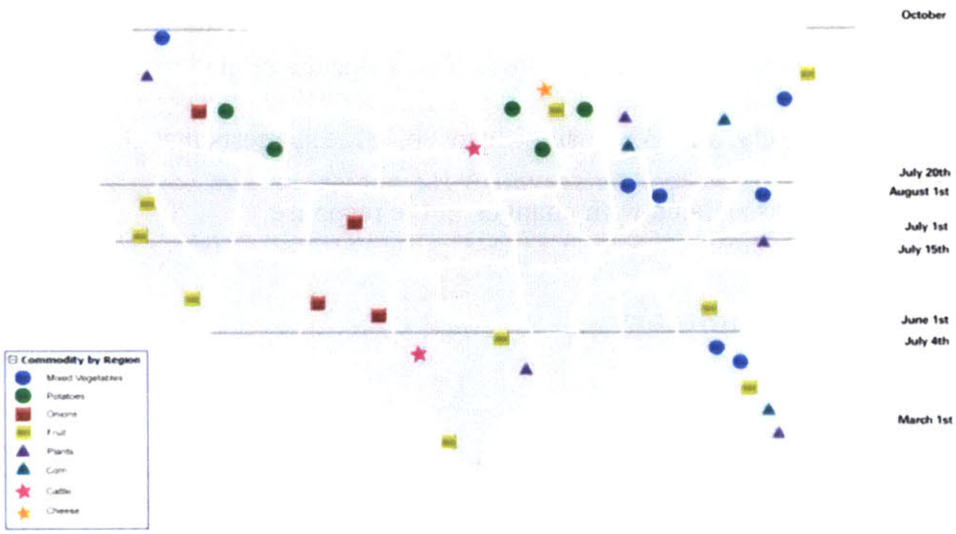

Figure 3: Commodity activity by region map (provided by ABC company)

Some regions have no agricultural activities, so for these regions this variable was not considered. For the regions with agricultural activity, this variable was considered as a binary variable (1 for the months with agricultural activity and 0 for the months without).

Regarding the number of trucks at origin, as we used monthly average cost per mile, we opted for using the truck capacity (number of trucks) from a region stand point, which means, the sum of trucks available per month at all states that compose that region. The number of trucks available was also provided by ABC Company, and does not capture the whole market. As the destinations are multiple for each region, we were not able to include the truck capacity at destination.

The p-value for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A low p-value (< 0.05) indicates that the null hypothesis can be rejected.

In other words, a predictor that has a low p-value is likely to be a meaningful addition to your model because changes in the predictor's value are related to changes in the response variable. Conversely, a larger (insignificant) p-value suggests that changes in the predictor are not associated with changes in the response.

4.7. Chapter summary

In this section we outlined the steps taken before analyzing the data and the tools we utilized to perform the analysis. We started with 1,609,594 rows of load shipments and ended up with 1,164,953 rows of data, which were later grouped in 7 different regions. The next chapter will discuss in more details the analyses performed on the resulted data and the results obtained through this process.

5. RESULTS

5.1. Data Exploration

The average rate per mile across ABC's network including fuel cost is not static. It changes with seasonality (weekly, monthly, quarterly, yearly) and has a general trend. This view is shown in Figure 4. The rates are normalized by dividing by the average cost per mile value.

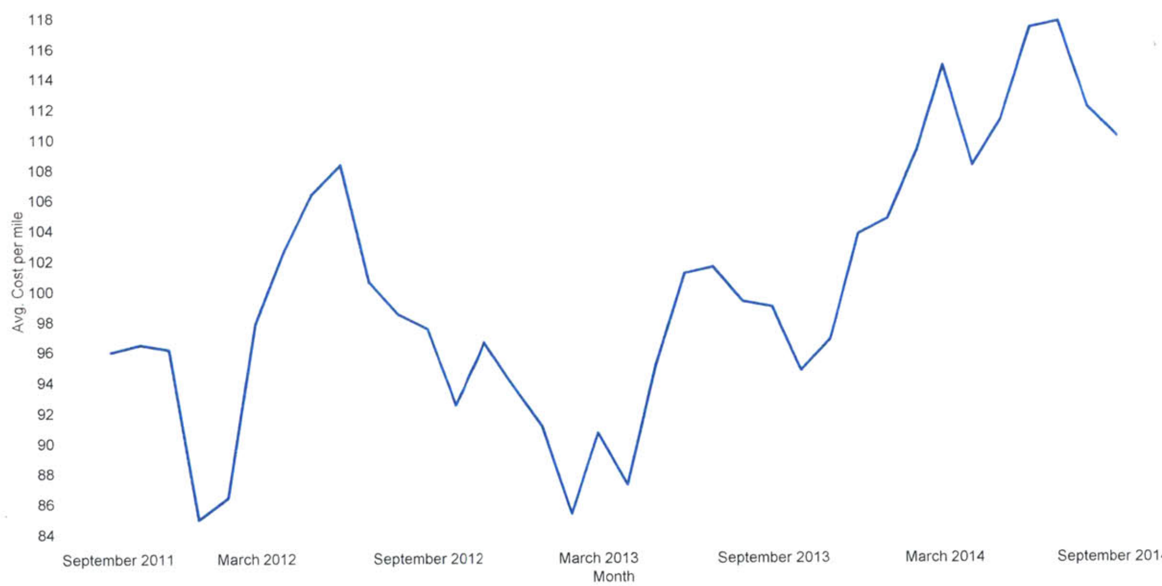

Figure 4: Average cost per mile including fuel costs

Typically, the peaks in the cost rates are occurring in the summer months and the dips are occurring in the winter months. However in the case of 2014, the dip is not prominent in the winter months likely due to harsh nation-wide weather conditions which put a pressure on the trucking industry, causing the rates to increase.

The cost per load is composed of the fuel cost and the linehaul cost. We are interested in the nature of the linehaul cost, and so the fuel cost must be removed. Figure 5 presents the monthly linehaul cost per mile across ABC's network after removing the fuel cost and normalizing with the average. We call this the national index and this forms the basis of the core analysis for spot market rates volatility.

Figure 5: National index

Similar to the previous average cost per mile visualization (with fuel prices), the national index in Figure 6 exhibits peaks during the summer months and dips during the winter months.

Once the data is separated by regions, using the Department of Energy Petroleum Administration for Defense Districts map (see Section 4), the regional indices are also generated. Figure 6 shows the monthly regional indices. The national index is plotted in black and bold in this graph for comparison.

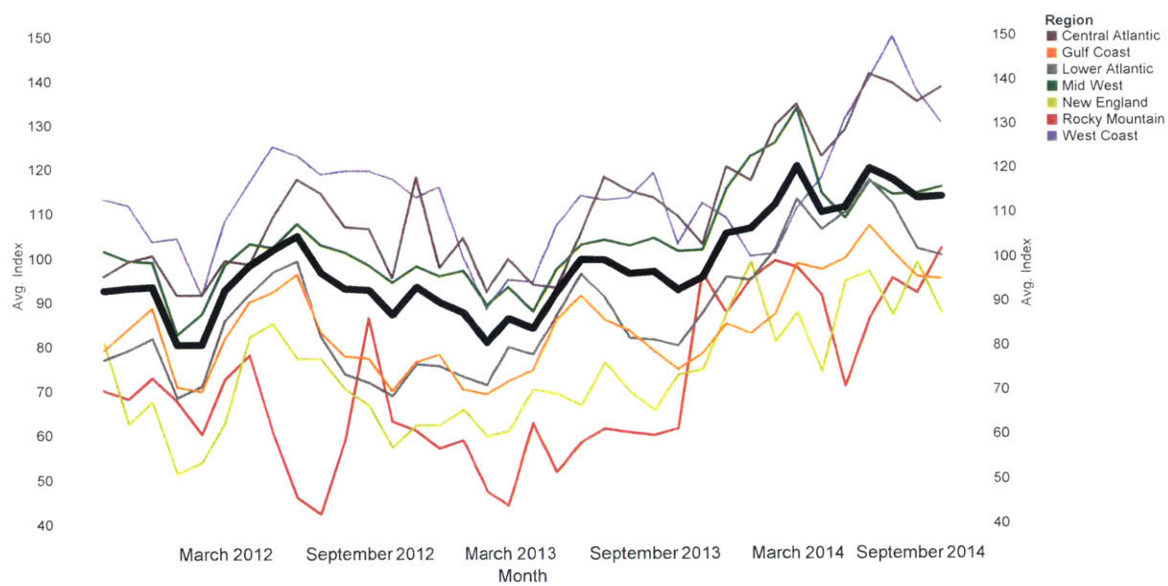

Figure 6: Regional indices and national index

As seen, on average, the Central Atlantic, Mid West and West Coast regions have a higher line haul cost than the national index. In addition, the New England and the Rocky Mountain regions appear to be more volatile than rest of the regions and the national index. These insights are supported by the average and coefficient of variation values calculated for each of the regions based on the monthly index as summarized in Table 4.

Table 4: Regional and national average and coefficient of variation

Region	**μ**	**CV**
National	100	21.4%
Central Atlantic	113	26.6%
Gulf Coast	87	31.3%
Lower Atlantic	90	24.7%
Mid West	107	21.0%
New England	73	49.0%
Rocky Mountain	68	72.0%
West Coast	114	30.5%

5.2. Distribution of Linehaul Cost per Mile

The historical cost per mile values of the national index are examined to determine an appropriate distribution fit. The probability distribution function is then utilized to determine the contract price that ABC should charge the shipper given that ABC would like to earn a margin of m dollars with a probability of p. If C is the cost per mile on a given lane and m is the desired margin with a probability of p, the contract price x can be determined as (i.e. $x - c >= m$) by solving the below equation:

$$P(C <= x - m) = p \tag{4}$$

The distributions for the different regions are outlined in Table 5 and are visualized in Figure 8.

Table 5: Regional probability density functions

Region	Distribution	Parameters
Central Atlantic	Dagum	k=8.4246, α=5.1365, β=0.82988
Gulf Coast	Lognormal (3 parameters)	σ=0.38336, μ=-0.4797, γ=0.69839
Lower Atlantic	Gamma (4 parameters)	k=0.59261, α=7.1229, β=0.01712, γ=1.0351
Mid West	Gamma (4 parameters)	k=0.48909, α=10.897, β=0.00377, γ=1.2343
New England	Burr (4 parameters)	k=0.4939, α=10.786, β=0.99944, γ=-0.0604
Rocky Mountain	Dagum (4 parameters)	k=2.0204, α=4.2097, β=0.45456, γ=0.39697
West Coast	Burr	k=0.71307, α=11.205, β=1.4189

Figure 7 shows that the line haul probability distributions differ for the various regions. Certain regions can be best fit by the Gamma distribution while others are best fit to the Log Normal, Burr and Dagum distributions. Importantly, it can be seen that none of the regions can be best fit to the normal distribution.

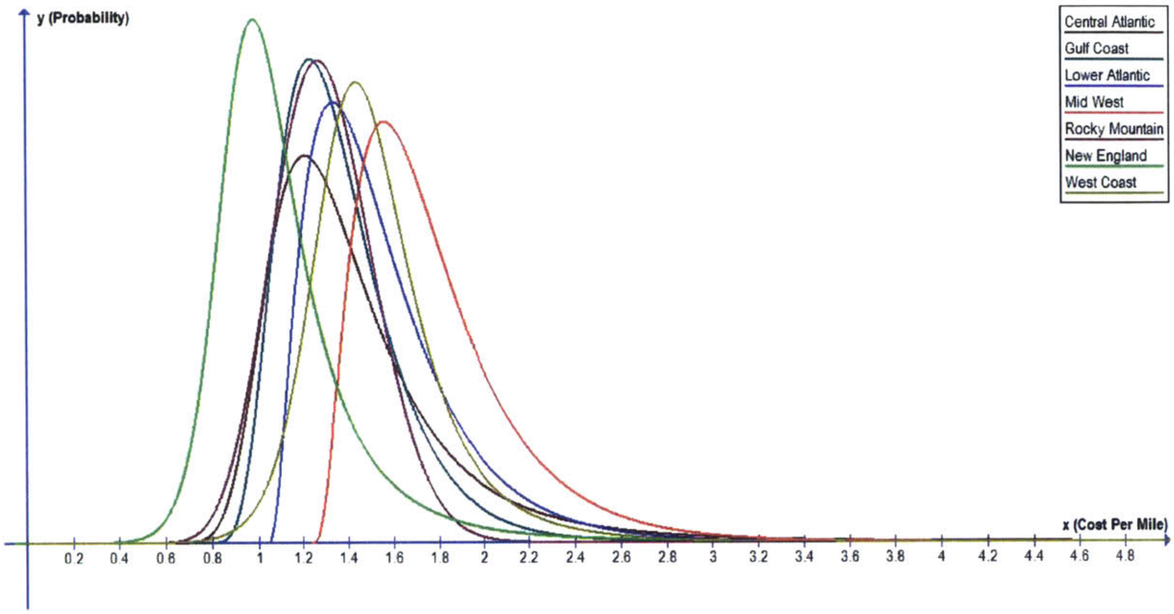

Figure 7: Regional line haul probability distributions

5.3. Volatility and Correlation

To quantify the volatility in the lanes, we calculate coefficient of variation, beta values and average month/month percentage change. The coefficient of variation for each of the regions is shown previously in Table 4.

The volatility of each of the regional indices is determined in comparison to the company national index. Table 6 below shows the regional betas in comparison with ABC company national index. Darker shades indicate high volatility. Green indicates that the price moves in the direction of the national index and orange indicates that price moves in the opposite direction of the index.

Table 6: Regional beta values (in comparison with national index)

Q	Central Atlantic	Gulf Coast	Lower Atlantic	Mid West	New England	Rocky Mountain	West Coast
2011Q4	2.06	1.58	1.17	0.95	0.36	-1.20	-0.75
2012Q1	0.99	1.13	0.91	1.09	1.35	1.12	0.40
2012Q2	1.36	-0.21	1.10	1.10	1.10	-0.93	1.77
2012Q3	0.57	0.64	1.07	0.80	0.07	4.93	1.14
2012Q4	0.73	0.89	1.06	1.08	1.59	0.11	1.03
2013Q1	1.36	0.80	0.54	0.99	0.54	1.08	1.24
2013Q2	1.26	1.29	0.86	0.79	-0.80	9.15	0.67
2013Q3	0.50	0.33	0.73	1.28	-0.52	4.22	1.33
2013Q4	0.79	1.86	0.93	0.73	-1.12	2.84	1.09
2014Q1	1.35	0.94	0.72	1.07	0.95	1.79	0.51
2014Q2	0.81	0.93	0.74	1.08	0.09	3.41	1.08
2014Q3	1.00	1.04	0.78	1.11	0.10	5.69	0.48
Overall	1.07	1.09	0.94	0.96	0.51	1.62	0.83

Figure 8 visualizes the volatility of regional indices in comparison with the national index as a function of time to better identify the trends in the volatility. It illustrates that the Rocky Mountain region is more volatile than the rest of the markets that ABC operates in. More specifically, Rocky Mountain peaks in Q3 2012 and Q2 2013. The peaks indicate that the rates are highly volatile in comparison to the national index, moving in the same direction as the national index. The New England region exhibits a high degree of volatility in Q2, Q3 and Q4 of 2013 however moving in the opposite direction of the national index. On the other hand, the Mid West and Lower Atlantic regions are flat and the beta values consistently hovering around 1 showing that both these regions behave identical to the national index of ABC and are stable in comparison to the national index.

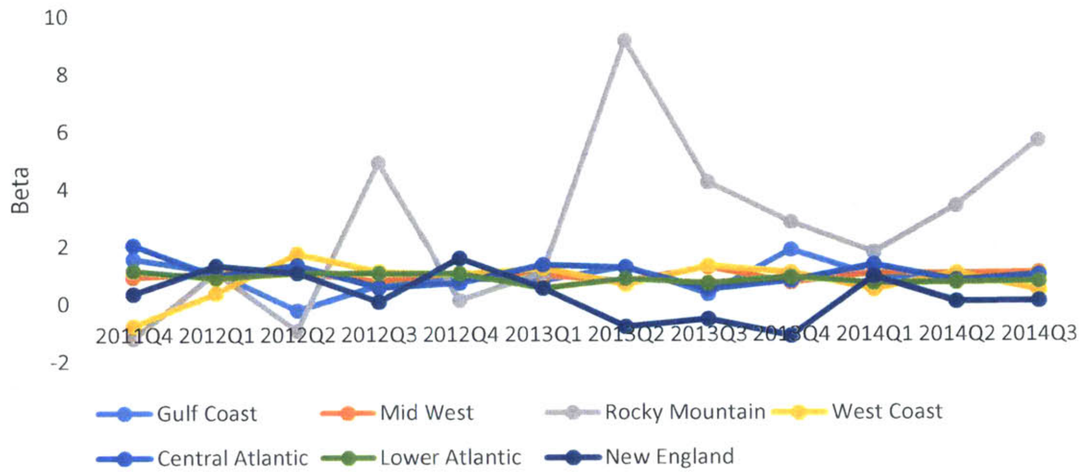

Figure 8: Volatility by beta of regional indices (in comparison with national index)

Next, as shown in Table 7, volatility is calculated by examining the average month over month percentage change in the monthly line haul rates. The New England and Rocky Mountain regions have a high average month over month percentage change than the other regions. This indicates that there are abrupt drops or peaks in the monthly line haul rates within these regions.

Table 7: Average month over month percentage changes

Region	**Average M/M percentage change**
National	1.51%
Central Atlantic	1.69%
Gulf Coast	1.21%
Lower Atlantic	1.48%
Mid West	1.67%
New England	4.32%
Rocky Mountain	5.17%
West Coast	1.30%

To further investigate the behavior of the line haul rates, the correlations are calculated between the national and regional indices. Table 8 shows the correlation between the national and regional indices for the entire timeframe of analysis.

Table 8: Correlation of national and regional indices (all data)

	National	*Central Atlantic*	*Gulf Coast*	*Lower Atlantic*	*Mid West*	*New England*	*Rocky Mountain*	*West Coast*
National	1.00							
Central Atlantic	0.84	1.00						
Gulf Coast	0.82	0.61	1.00					
Lower Atlantic	0.84	0.59	0.83	1.00				
Mid West	0.87	0.65	0.59	0.63	1.00			
New England	0.35	0.41	0.22	0.20	0.27	1.00		
Rocky Mountain	0.18	0.09	0.16	0.04	0.03	0.05	1.00	
West Coast	0.71	0.60	0.61	0.63	0.44	0.14	0.12	1.00

The correlations demonstrates that the Mid West region most closely resembles the national index when considering the entire duration of analysis. However when examining individual years for instance 2012 as shown in Table 8, the Central Atlantic, Gulf Coast and Lower Atlantic regions also quite closely resemble the national index.

Table 9: Correlation of national and regional indices (2012)

	National	*Central Atlantic*	*Gulf Coast*	*Lower Atlantic*	*Mid West*	*New England*	*Rocky Mountain*	*West Coast*
National	1.00							
Central Atlantic	0.86	1.00						
Gulf Coast	0.88	0.67	1.00					
Lower Atlantic	0.86	0.64	0.82	1.00				
Mid West	0.78	0.62	0.60	0.59	1.00			
New England	0.54	0.34	0.44	0.61	0.47	1.00		
Rocky Mountain	0.12	-0.03	0.17	-0.05	-0.13	-0.18	1.00	
West Coast	0.72	0.70	0.65	0.66	0.23	0.32	0.10	1.00

After considering the correlation in 2013 as well as shown in Table 10, it can be inferred that the Rocky Mountain followed by New England behave differently from the national index and all the other regions that ABC operates in. One plausible explanation is the low volume of truck loads in these regions. In addition, within the East Coast Region, the sub-regions Central Atlantic, Lower Atlantic and New England behave differently when compared to each other.

Table 10: Correlation of national and regional indices (2013)

	National	Central Atlantic	Gulf Coast	Lower Atlantic	Mid West	New England	Rocky Mountain	West Coast
National	1.00							
Central Atlantic	0.78	1.00						
Gulf Coast	0.84	0.54	1.00					
Lower Atlantic	0.79	0.36	0.83	1.00				
Mid West	0.89	0.58	0.69	0.65	1.00			
New England	0.35	0.75	0.20	0.05	0.10	1.00		
Rocky Mountain	0.23	0.34	0.26	0.08	0.01	0.32	1.00	
West Coast	0.72	0.48	0.47	0.62	0.54	0.08	0.22	1.00

Next, the national and regional indices are compared against the CASS index. This index is managed by the company Cass Information Systems Inc. and represents the CASS Truckload Linehaul Index. As the nation's largest payer of freight bills, CASS manages more than $26 billion annually in freight spend, enabling CASS to compile meaningful logistics data that serves as an indicator of transportation industry trends. The CASS Truckload Linehaul Index™ is a measure of market fluctuations in per-mile truckload linehaul rates, independent of additional cost components such as fuel and accessorials, providing an accurate reflection of trends in baseline truckload prices. The index uses January 2005 as its base month.

Table 11 illustrates the beta values when comparing the national and regional indices with the CASS index. The beta values are calculated for 2012 and 2013 using the monthly indices. As it can be seen, the national index moves in the direction of the CASS index in 2013 but the opposite direction in 2012.

Table 11: CASS beta values in comparison with national and regional indices

Index	2012	2013
National	-0.93	0.78
Central Atlantic	-2.40	0.49
Gulf Coast	0.97	0.46
Lower Atlantic	0.31	0.54
Mid West	-1.31	0.90
New England	-1.19	-0.98
Rocky Mountain	10.64	2.26
West Coast	-2.04	0.54

To further investigate the behavior of the national and regional indices with respect to the CASS index, the correlations are calculated for all years as shown in Table 12.

Table 12: Correlation of national and regional indices with CASS index (all data)

	CASS	*National*	*Central Atlantic*	*Gulf Coast*	*Lower Atlantic*	*Mid West*	*New England*	*Rocky Mountain*	*West Coast*
CASS	1.00								
National	0.14	1.00							
Central Atlantic	-0.04	0.84	1.00						
Gulf Coast	0.27	0.82	0.61	1.00					
Lower Atlantic	0.16	0.84	0.59	0.83	1.00				
Mid West	0.13	0.87	0.65	0.59	0.63	1.00			
New England	0.00	0.35	0.41	0.22	0.20	0.27	1.00		
Rocky Mountain	0.22	0.18	0.09	0.16	0.04	0.03	-0.05	1.00	
West Coast	0.06	0.71	0.60	0.61	0.63	0.44	0.14	0.12	1.00

As seen in Table 12, the ABC national index behaves distinctly different from the CASS national index and both the indices are uncorrelated. This is because the correlation between national and CASS is only 0.14 and for most regions and CASS is less than 0.25. Therefore the CASS index is not a good representation of ABC's business. Hence we use ABC's national index for our Beta calculations when examining the volatility and risk for different regions and lanes.

5.4. Lane Characterization

A framework for lane characterization is outlined in Figure 9. According to the framework, the top 10 risky and less risky lanes are identified by each type of volatility i.e. coefficient of variation, beta and average month over month percentage change. This is done for both short haul (≤250 miles) and long haul (>250 miles) lanes. The results are included in the appendix.

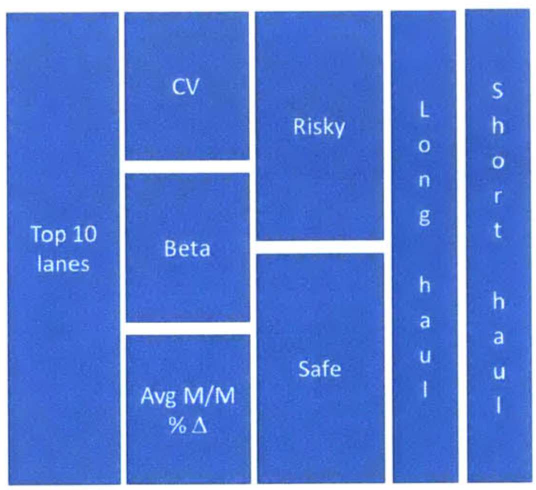

Figure 9: Lane characterization framework

In general, the Lower Atlantic region consists of more high risk long-haul lanes than any other region that ABC operates in, based on all three measures of volatility. The Mid West region consists of more high risk short-term lanes than any other region that ABC operates in. In addition, the Lower Atlantic region consists of more low risk long-haul lanes than any other region that ABC operates in, based on all three measures of volatility and the Central Atlantic region consists of more low risk short-haul lanes than the other regions.

5.5. Factors Related to Volatility

- Beta vs. Distance

  Here, beta for each of the lanes in the sample is plotted against the distance of the lane to investigate the relationship between volatility and distance as shown in Figure 10.

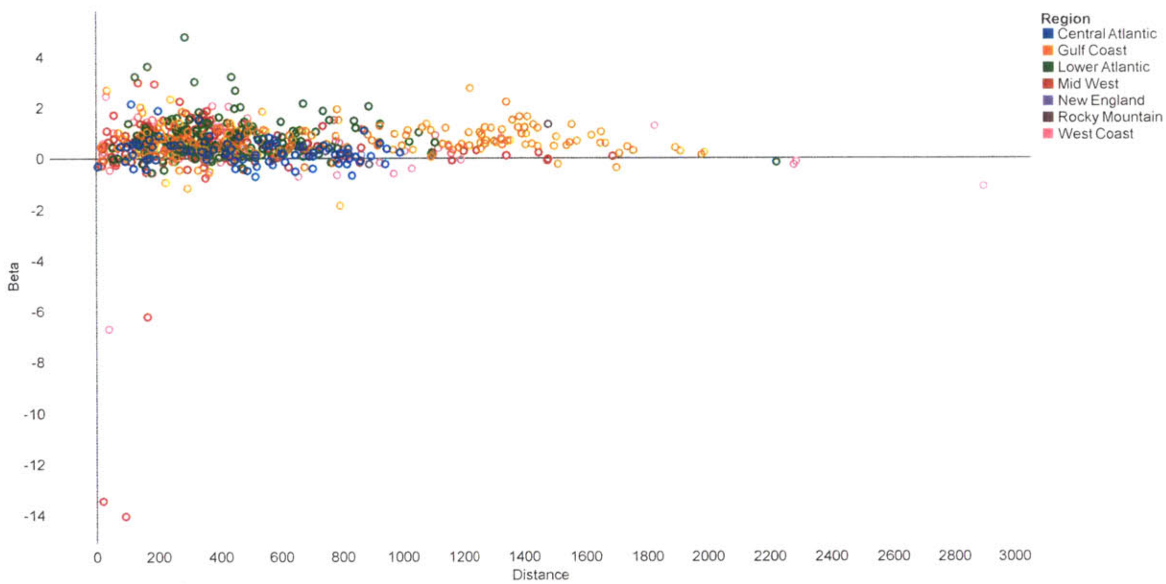

Figure 10: Beta vs. distance

The R-squared value and the p-value for the overall model for Beta vs. Distance are 0.04 and 0.02 respectively. This indicates that there the model is insignificant. The p-values for the various region trend lines (slope coefficient) are in Table 13.

Table 13: Region p-values – beta vs. distance

Region	P-value
West Coast	0.26
Rocky Mountain	0.16
New England	0.41
Mid West	0.54
Lower Atlantic	0.79
Gulf Coast	0.36
Central Atlantic	0.06

- Coefficient of Variation vs. Distance

  Here, coefficient of variation for each of the lanes in the sample is plotted against the distance of the lane to investigate the relationship between volatility and distance as shown in Figure 11.

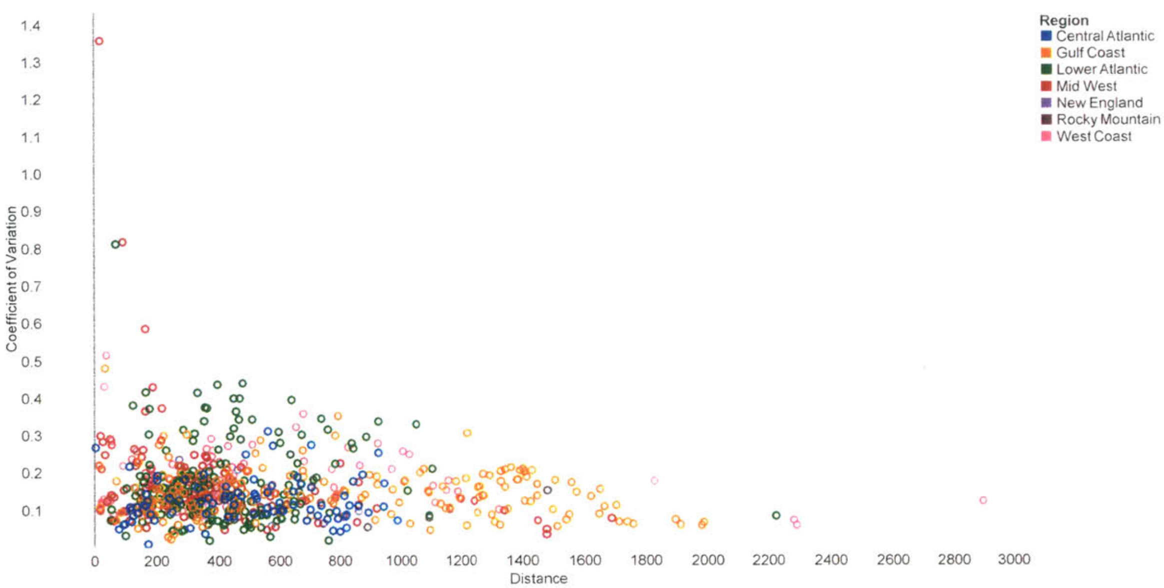

Figure 11: Coefficient of variation vs. distance

The R-squared value and the p-value for the overall model for Coefficient of Variation vs. Distance are 0.08 and >0.0001 respectively. This indicates that the model is insignificant. The p-values for the various region trend lines (slope coefficient) are in Table 14.

Table 14: Region p-values – coefficient of variation vs. distance

Region	**P-value**
West Coast	0.14
Rocky Mountain	0.06
New England	0.14
Mid West	0.00
Lower Atlantic	0.78
Gulf Coast	0.23
Central Atlantic	0.66

Based on both the beta values and the coefficient of variation, there is no strong evidence to suggest that volatility reduces with an increase in distance across all the regions. However in the case of the Mid West region, the volatility reduces as the distance increases based on the coefficient of variation as indicated by the low p-value.

- Beta vs. Volume

  Here, beta for each of the lanes in the sample is plotted against the volume of the lane to investigate the relationship between volatility and volume as shown in Figure 12.

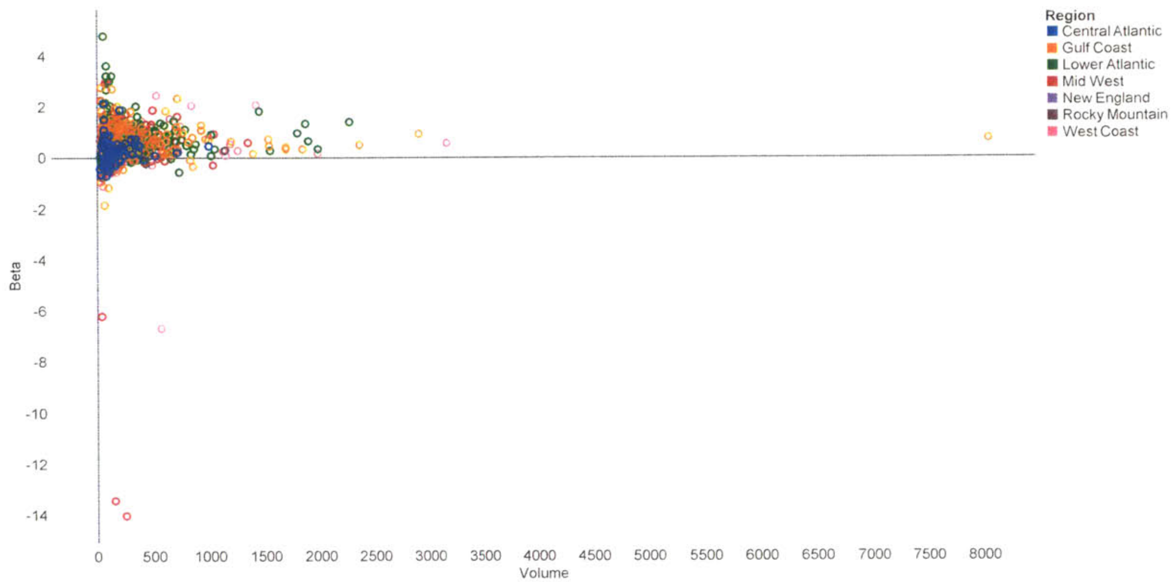

Figure 12: Beta vs. volume

The R-squared value and the p-value for the overall model for Beta vs. Volume are 0.03 and 0.03 respectively. This indicates that the model is insignificant. The p-values for the various region trend lines (slope coefficient) are shown in Table 15.

Table 15: Region p-values – beta vs. volume

Region	**P-value**
West Coast	0.67
Rocky Mountain	0.47
New England	0.09
Mid West	0.59
Lower Atlantic	0.70
Gulf Coast	0.84
Central Atlantic	0.57

- Coefficient of Variation vs. Volume

  Here, coefficient of variation for each of the lanes in the sample is plotted against the volume of the lane to investigate the relationship between volatility and volume.

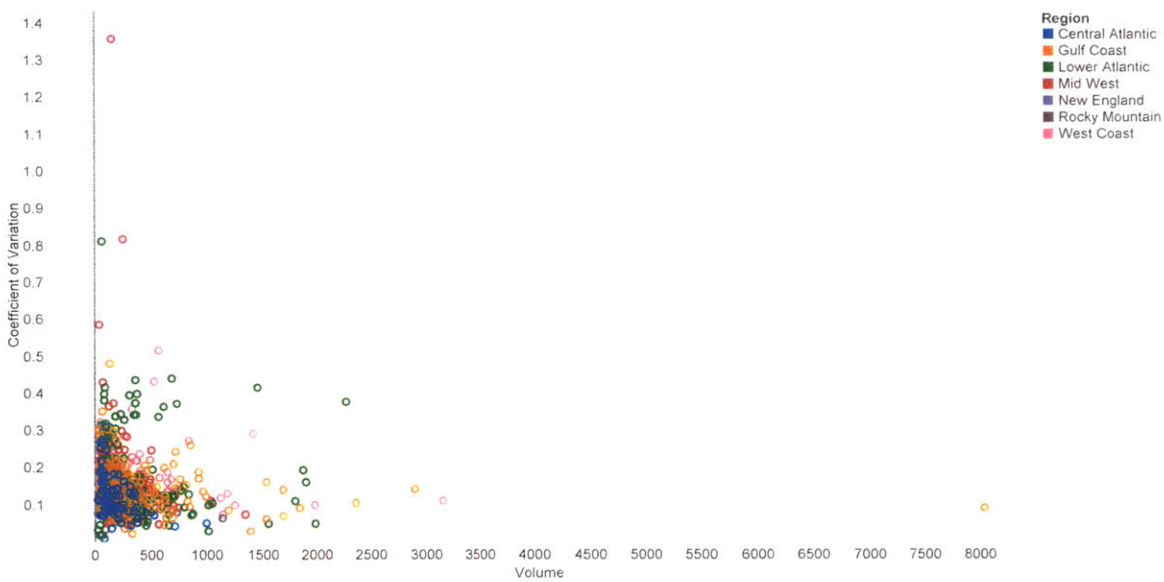

Figure 13: Coefficient of variation vs. volume

The R-squared value and the p-value for the overall model for Coefficient of Variation vs. Volume are 0.07 and >0.0001 respectively. This indicates that the model is insignificant. The p-values for the various region trend lines (slope coefficient) are shown in Table 16.

Table 16: Region p-values – coefficient of variation vs. volume

Region	**P-value**
West Coast	0.11
Rocky Mountain	0.29
New England	0.99
Mid West	0.03
Lower Atlantic	0.29
Gulf Coast	0.02
Central Atlantic	<0.0001

Based on both the beta values and the coefficient of variation, there is evidence to indicate that volatility reduces with an increase in volume for the Mid West, Gulf Coast and Central Atlantic regions. In the remaining regions, the volume does not influence the volatility.

5.5.1. Risk Profiles

For the 674 lanes that are analyzed and characterized, the figures (from 24 to 32) below show the risk profiles at national and regional level based on all three volatility measures (beta, coefficient of variation and average M/M change, respectively). The risk profiles are histograms indicating the spread and frequencies of the volatility measures among the 674 sample lanes analyzed based on 2012 and 2013 data. Figure 14 shows the risk profile for the overall nation based on beta as a measure of risk. A higher proportion of lanes fall within the beta value of -1 and 1 indicating that a large number of lanes are less volatile than the overall national index. The end points of -14.1 and 4.7 indicate that there are a small number of highly volatile lanes. The missing values are omitted (e.g. beta = -0.5) in order to display the outliers in the view.

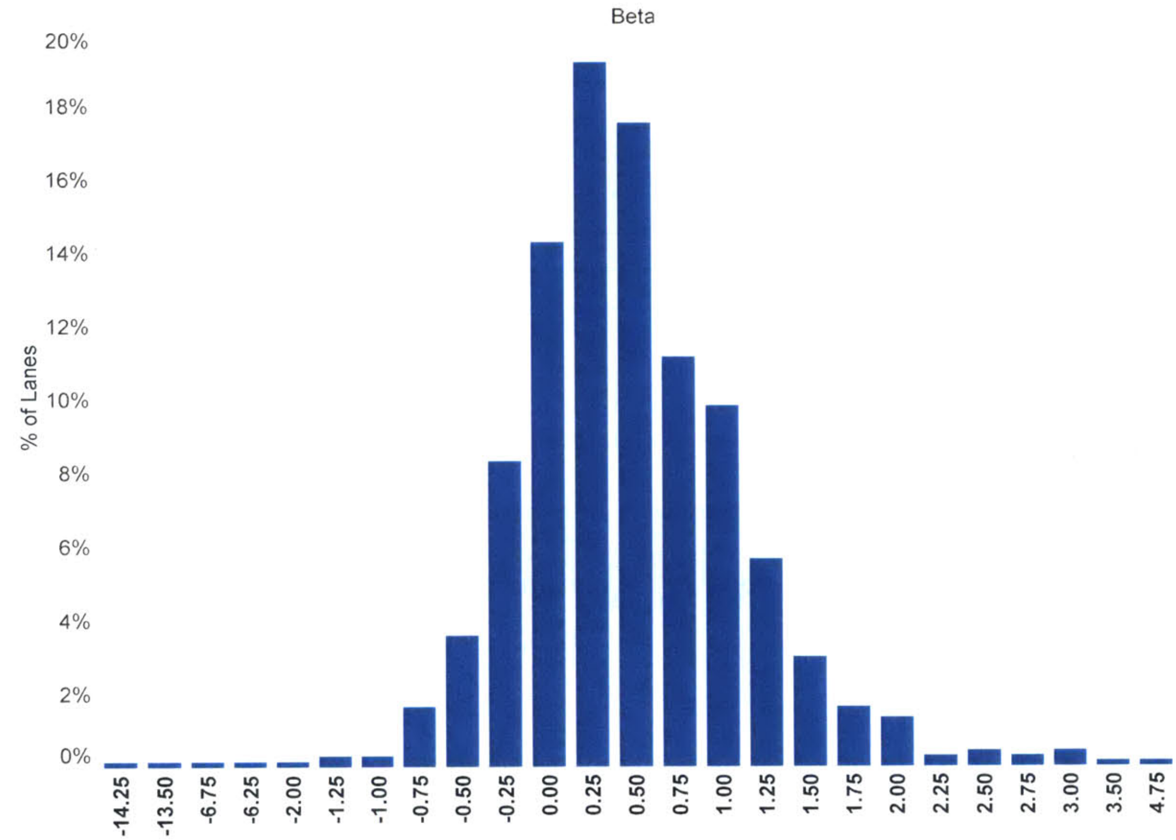

Figure 14: National risk profile (2012 and 2013 beta)

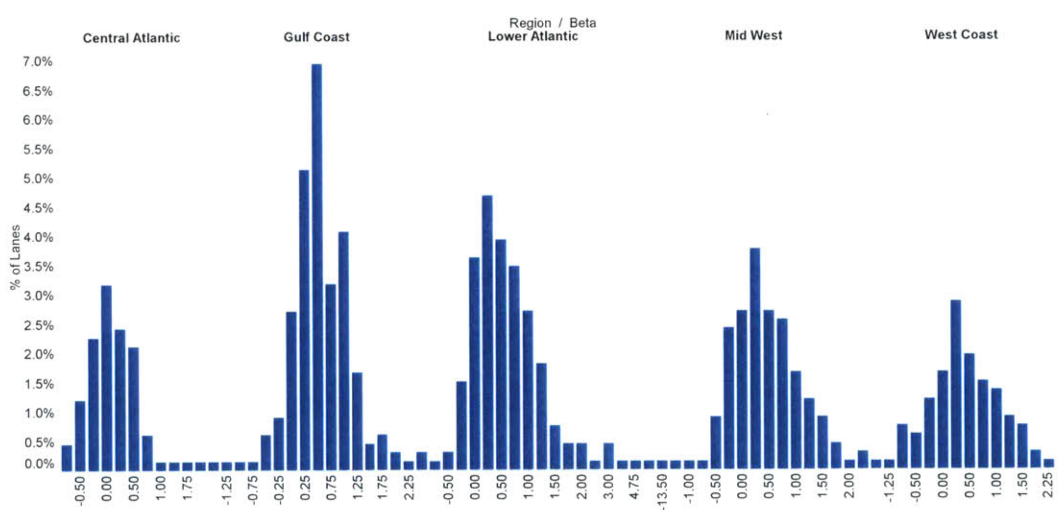

Figure 15: Regional risk profile (2012 and 2013 beta)

Figures 15 illustrates the volatility profiles for the various regions. Among the different regions, the Central Atlantic appears to be less volatile due to the lower spread of the beta values. The New England and Rocky Mountain regions have beta values close to 0 indicating that they are uncorrelated to the national index.

Figure 16 shows the national risk profile based on coefficient of variation as a measure of risk. A large proportion of lanes are between 0.025 and 0.25 indicating overall stability. However a small number of lanes are highly volatile as indicated by a coefficient of variation of more than 0.25.

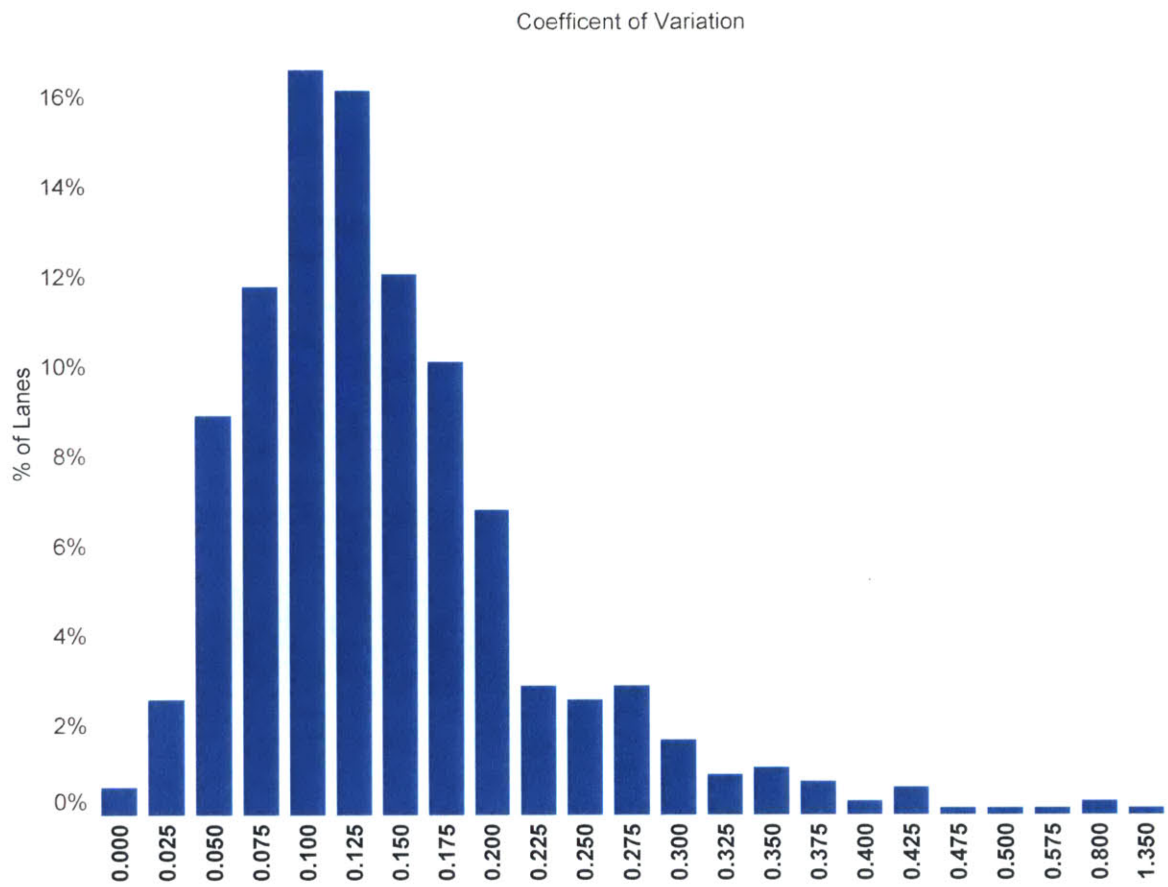

Figure 16: National risk profile (2012 and 2013 coefficient of variation)

In addition to the national risk profile, the regional risk profile is shown in Figure 17. Based on the regional profiles, the Mid West region has the highest spread followed by the Lower Atlantic region.

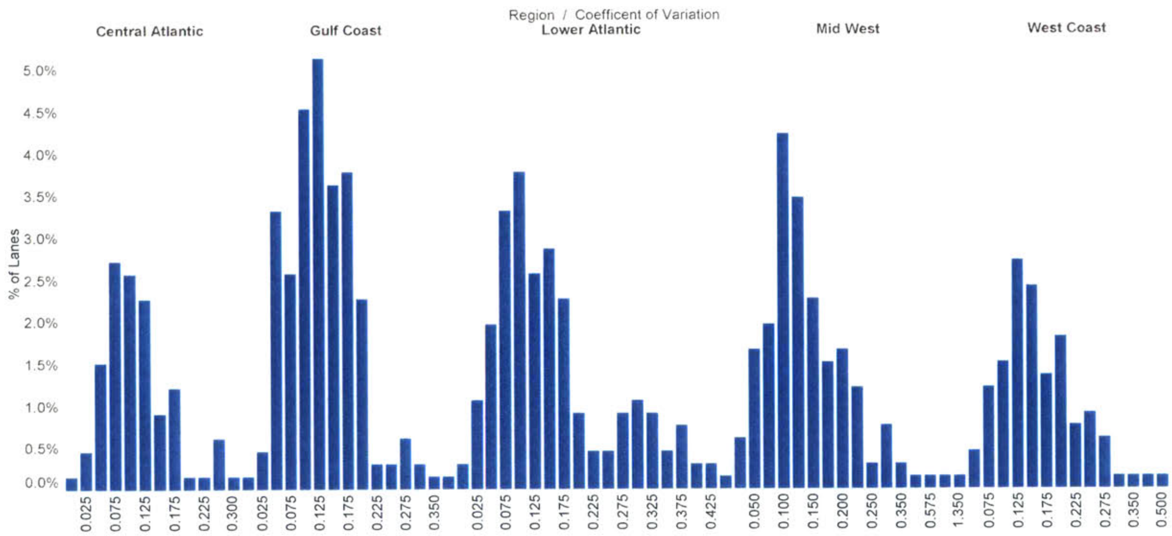

Figure 17: Regional risk profile (2012 and 2013 coefficient of variation)

Figure 18 shows the national risk profile based on the average month/month percentage changes in the linehaul cost per mile rates. As seen there are some lanes with extreme values of more than 100%, exhibiting the sporadic movement of spot market rates in such lanes.

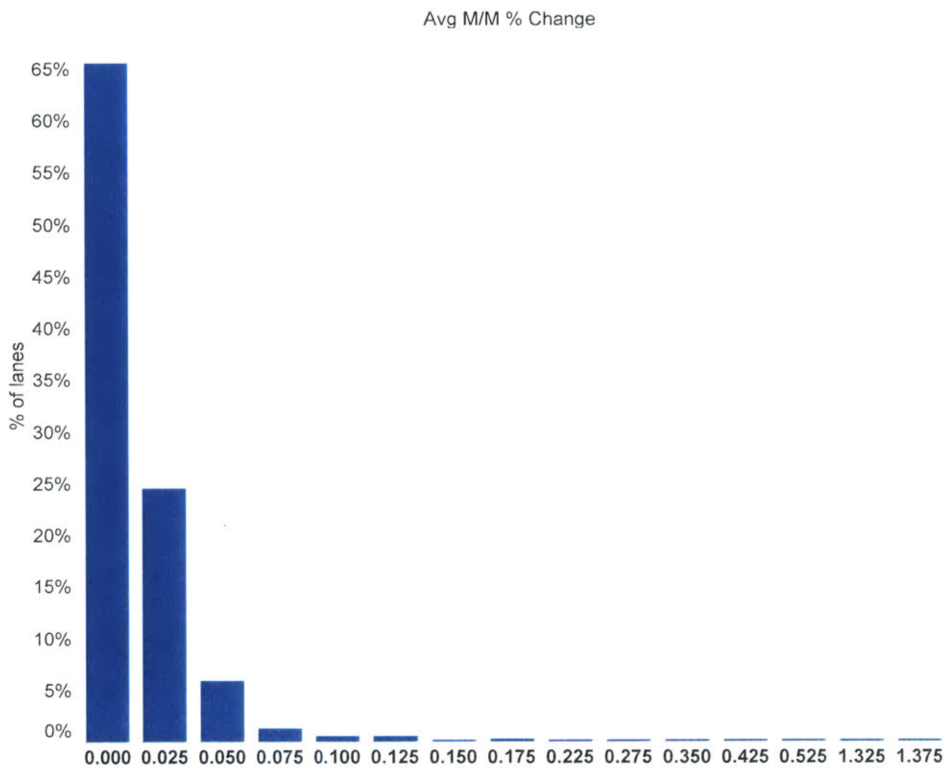

Figure 18: National risk profile (2012 and 2013 average M/M % change)

Of the various regions shown in Figures 19, the Mid West region has the highest spread in this measure.

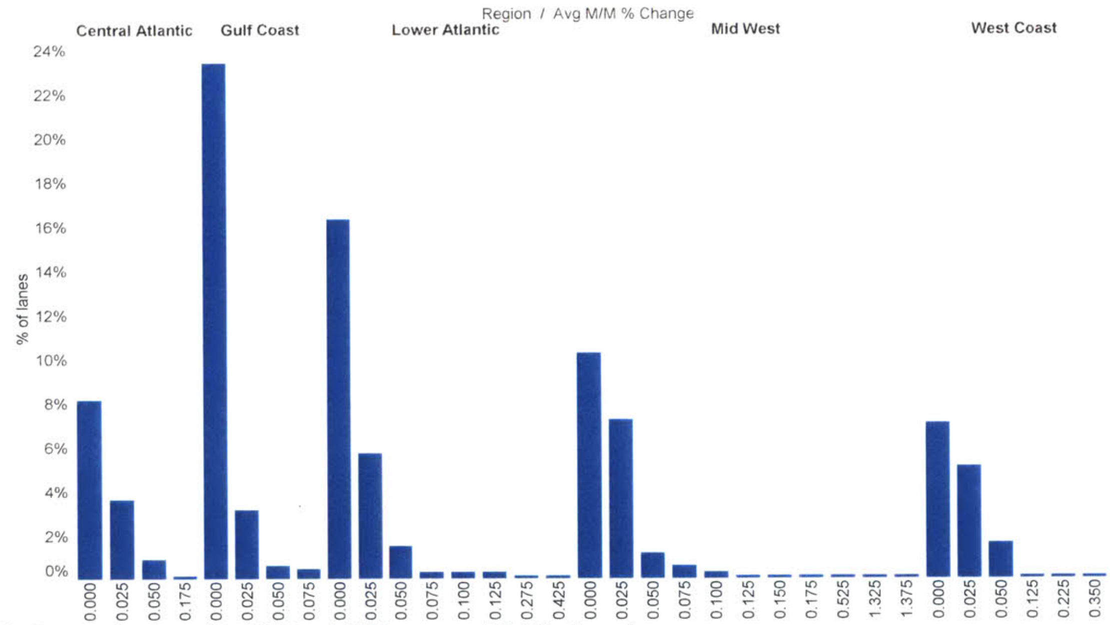

Figure 19: Regional risk profile (2012 and 2013 average M/M % change)

5.6. Regression Analysis

Table 17 below shows the regression analysis results obtained using the monthly average cost per mile in years 2012 and 2013 for each region (Central Atlantic, Lower Atlantic, New England, Gulf Coast, West Coast, Mid-West, and Rocky Mountain).

Table 17: Regression analysis summary

			P-values				
Region	R Square	Adjusted R Square	Intercept	Month/Year	GDP Index	# trucks @ Origin	Commodities Seasons
Central Atlantic	0.17	0.09	0.88	Excluded	0.37	0.15	Excluded
Gulf Coast	0.56	0.51	0.00	Excluded	Excluded	0.05	0.00
Lower Atlantic	0.57	0.53	0.00	Excluded	Excluded	0.06	0.00
Mid West	0.51	0.44	0.35	0.31	0.14	0.00	Excluded
New England	0.15	0.07	0.85	Excluded	0.50	0.16	Excluded
Rocky Mountain	0.12	-0.01	0.25	Excluded	Excluded	0.70	0.36
West Coast	0.21	0.14	0.61	Excluded	0.23	Excluded	0.07

During the regression analysis, it was observed that each region behaves differently, which was already expected based on the other analysis performed during this research. The variable or set of variables that influence(s) one region does not necessarily influence(s) the other. Crop seasons plays a role in some regions (e.g. Gulf Coast and Lower Atlantic) but does not play in others (e.g. Rocky Mountain). The same happens with truck capacity, GDP index, etc.

As mentioned previously in the literature review section, executives and specialists believe that volatility, uncertainty and imbalance of the trucking spot market are caused as a result of various factors such as shortage of truck drivers, rising and fluctuating fuel costs, increasingly constrained regulatory environment, extreme weather, increasing operating costs, and many others uncontrollable factors. Most factors are not easily available to the public, or are not available at all, such as carrier's strategies and decisions, or even a truck driver's desire to go back home.

Despite the low results in terms of R square, the regression analysis was useful to give a sense of how different regions are influenced by different reasons. Once companies understand that, it is possible to put these factors into account when expanding their business or when agreeing into a long-term contract with a new client, as they could establish different rates for different times of the year in regions where agricultural activities play a role for example.

6. INSIGHTS AND CONCLUSION

Based on the data analysis in chapter 5, in this section we summarize the key findings of our research and discuss related recommendations. We propose a series of methods truckload service providers can use in order to assess and address the risk involved in their operations.

We will first present the key findings of this research, followed by an example application of the research in supporting contract pricing and a list of useful recommendations for assessing and evaluating risk in trucking market operations.

6.1. Key Findings

The different regions as separated based on the Department of Energy Petroleum Administration for Defense Districts map have unique indices which behave differently over the timeframe. Based on the three risk measures calculated to determine the volatility (coefficient of variation, beta and average month/month percentage change), the Rocky Mountain region is more volatile than the rest of the markets that ABC operates in. On the other hand, the Mid West and Lower Atlantic regions are stable and have a similar behavior to the ABC national index.

Correlation analysis during the entire duration of analysis demonstrates that the Central Atlantic, Gulf Coast, Lower Atlantic and Mid-West regions closely resemble the national index. Rocky Mountain and New England regions have a low correlation to the national index. The national and regional indices have a very low correlation to the CASS index which is an index managed by the company Cass Information Systems Inc. and represents the Cass Truckload Linehaul Index for the overall market demonstrating that

ABC's business is different from rest of the industry and that the CASS index is not an appropriate representation of its business.

Based on the volatility measured by beta values and the coefficient of variation, it is found that the Lower Atlantic region consists of the most high risk long haul lanes than any other region that ABC conducts business in, even though the region as a whole is flat and stable. In addition, the Mid West region consists of the most high risk short-haul lanes than any other region that ABC operates in based on both the beta value and the coefficient of variation even though the region as a whole is flat and stable. The Lower Atlantic region also consists of the most number of low risk long-haul lanes. The most number of low risk short-haul lanes are present in the Central Atlantic region which closely resembles the national index.

The top risky lanes for ABC's business based on 2012 and 2013 measures of volatility for both short haul and long haul lanes are listed in Table 18.

Table 18: Top risky lanes for ABC company

Lanes	**Origin**	**Destination**
303-397	Atlanta	Columbus
985-956	Olympia	Sacramento
852-902	Phoenix	Inglewood
799-906	El Paso	Long Beach
775-581	North Houston	Fargo
775-559	North Houston	Rochester
480-461	Royal Oak	Indianapolis
463-410	Gary	Cincinnati
440-461	Cleveland	Indianapolis
336-303	Tampa	Atlanta
330-303	Southern Florida	Atlanta
328-300	Orlando	Atlanta
320-395	Jacksonville	Gulfport
320-361	Jacksonville	Montgomery
320-354	Jacksonville	Tuscaloosa
320-303	Jacksonville	Atlanta
320-300	Jacksonville	Atlanta
320-280	Jacksonville	Charlotte
313-241	Savannah	Roanoke
302-386	Atlanta	Hickory
300-469	Atlanta	Kokomo
300-272	Atlanta	Greensboro
295-604	Florence	Chicago
070-281	Newark	Charlotte

The regression analysis indicates that the relationship between volatility (measured in both Beta and coefficient of variation) and distance is not significant. Therefore there is no strong evidence to suggest that volatility reduces with an increase in distance. However the exception to this is the Mid-West region where the low p-value suggests that volatility indeed reduces with an increase in distance i.e. the longer the lanes are, the less volatile the cost rates. In the case of volatility and volume, the evidence suggests that volatility reduces with an increase in volume of loads in the Mid-West, Central Atlantic and Gulf Coast regions. For the remaining regions there is no significant relationship to indicate that volatility is influenced by volume.

Commodities play an influential role in effecting the prices in the Lower Atlantic and Gulf Coast regions which could be evidenced in both the regression of the overall regions as well as particular lanes in the regions. For the Mid-West and Gulf Coast regions, the number of trucks available at the region influences the rates while in the other regions this is not significant factor of influence. However this may not be necessarily true for particular lanes in the region. Neither GDP index performance nor the time of the year play an important role in effecting the rates across the regions as a whole. However in certain lanes for example the lane from the city Industry in California to the city Industry in California i.e. 917-917 (3-digit origin/destination), GDP index influences the cost rates. This is because in industrial cities the GDP greatly impacts the industrial activities. The lower R-square values in the regression analysis of the rates for the lanes and regions indicate that there are additional factors that influence the rates other than the GDP, time of the year, truck capacity and commodities activities.

6.2. Management Implementation

The risk profiles for the various risk measures can used as a guidance for classifying the lanes in terms of risk. To demonstrate the application of the research to price long-term contracts, the lane Laredo to Houston is considered for analysis. The Laredo to Houston lane is indicated by the 3 digit lane 780 to 770 based on the zip code aggregation method and belongs to the Gulf Coast region.

The average distance for this 3 digit lane is 350 miles and the total volume of loads is 1977 during 2012 and 2013. This implies that the lane is long-haul and high volume. Figure 20 indicates the monthly change in linehaul cost per mile for the lane.

Figure 20: Monthly cost per mile – Laredo x Houston (lane 780 – 770)

The coefficient of variation was 14%, the beta was 0.92 and the percentage month/month change was 1.07%. The coefficient of variation is lower than the national and Gulf Coast for long-haul lanes. The beta in comparison with the national index is close to 1 indicating that it moves in the same direction and is less volatile than the national index. The percentage month/month change is also less than the national and Gulf Coast averages. Additionally, all three measures of volatility are within the thresholds established for risk classification as seen in Table 19. This indicates that the lane is less volatile than the national index of ABC and is a relatively safe lane to carry out business in comparison to the overall network. In addition, the degree of variation exhibited in this lane is lower than its region and the overall network.

Figure 21 indicates the weekly change in linehaul cost per mile for the lane. The weekly coefficient of variation is 15%, the average week over week percentage change is 0.26% and the weekly beta when compared to the weekly national index is 0.01.

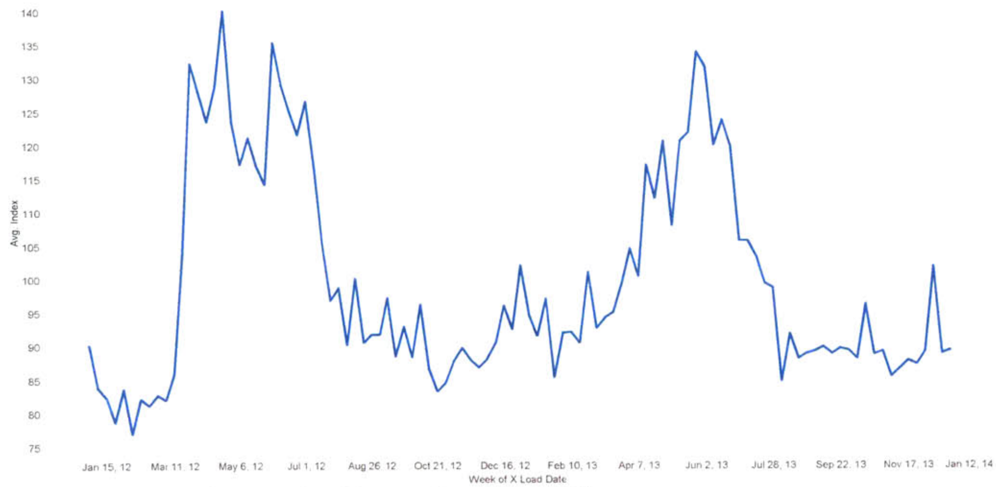

Figure 21: Weekly cost per mile – Laredo x Houston (lane 780 – 770)

Figure 22 indicates the daily change in linehaul cost per mile for the lane. The daily coefficient of variation is 27%. As expected this is higher than weekly and monthly due to the transactional nature of the spot market.

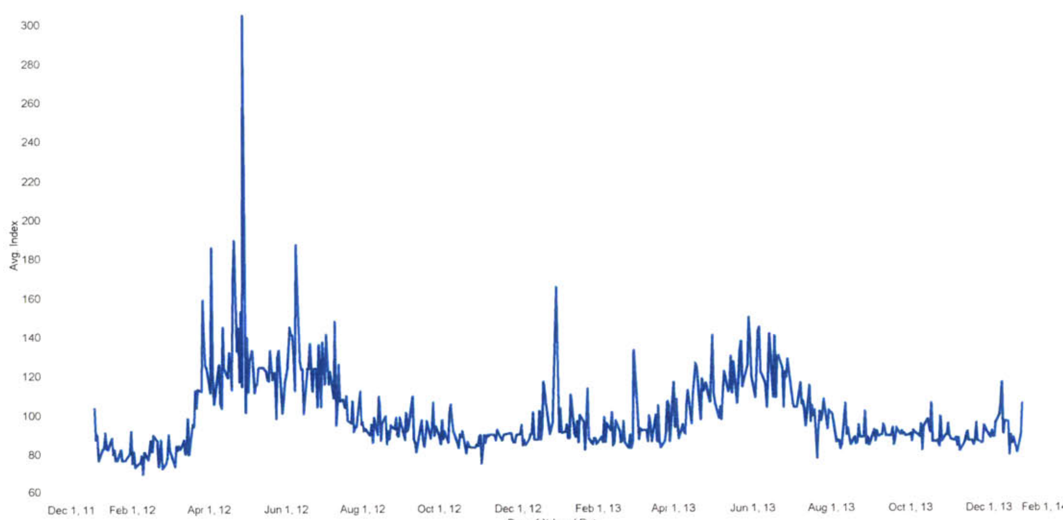

Figure 22: Daily cost per mile – Laredo x Houston (lane 780 – 770)

A distribution fit is performed for the historical cost per mile line haul rates. The resulting distribution based on goodness of fit using the chi-squared test is the Burr (4P).

The parameters for this distribution are k=0.17195, α=30.958, β=1.2739 and γ=-0.2709. This is shown in Figure 23.

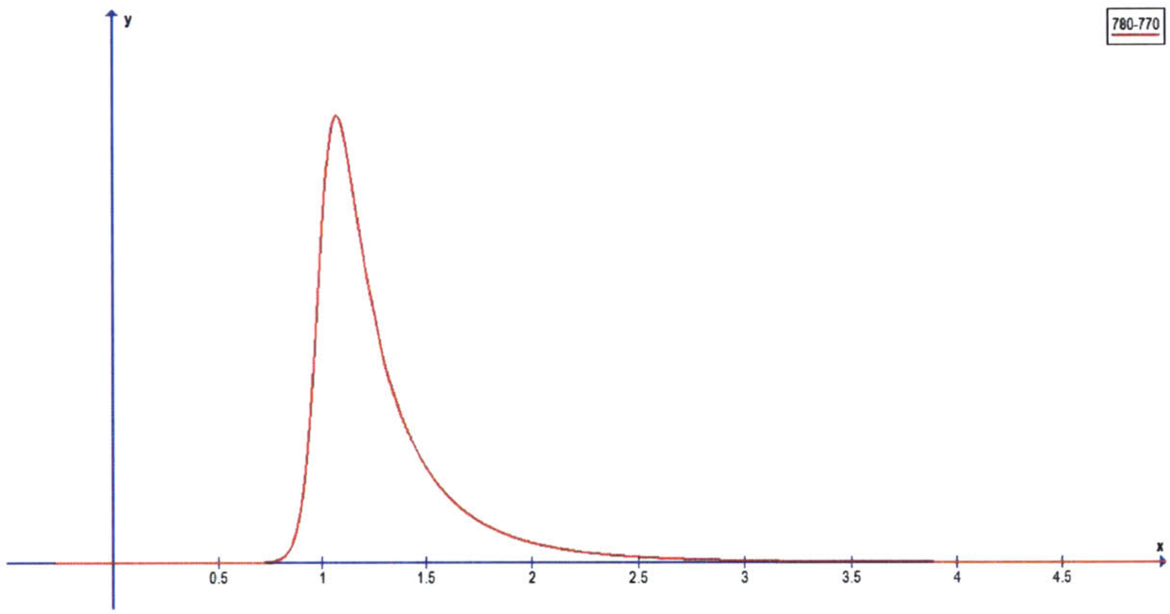

Figure 23: Probability density function – Burr (Laredo x Houston)

Based on this information for this particular lane:

- For 75% chance to break even set the contract price to $1.38
- For 90% chance to break even set the contract price to $1.70
- For 95% chance to break even set the contract price to $1.97
- Any additional margin should be added on top of the above

In addition, based on the regression analysis, it was found that the truck capacity at origin and agricultural patterns are significant factors in influencing the spot market rates. Therefore, when pricing the contract with the shipper, it must be determined whether the shipper intends to ship any loads during the agricultural season. If that is true, an appropriate premium has to be placed on the prices for the season.

6.3. Recommendations and Conclusion

Below are key recommendations for 3PL businesses:

Volatility characterization is holistic: As seen in the analysis, it is essential to take a holistic approach when assessing volatility and risk. In this case three measures i.e. coefficient of variation, beta and average month/month percentage change were developed to quantify the volatility in lanes and regions and characterize them. This ensured that though a lane may appear to be "safe" under one type of volatility measure, its "risk" as measured by another type of volatility measure is accurately captured.

Volatility characterization is geographic: As seen in the analysis, volatility varies geographically across the various regions. Some regions such as the Rocky Mountain and New England are evidently more volatile than rest of the markets. Hence, it is important to view the regional differences in volatility when assessing the risk faced by the 3PL business. In situations where individual lanes do not follow the regional characteristics, sub-region categorization and individual lane based volatility analysis will help improve the precision.

Volatility factors vary geographically: The factors that influence the volatility in one region or lane do not necessarily impact the other regions or lanes. Hence, the factors have to be tested for their influence across the various regions and lanes to understand volatility patterns.

Our key contributions from this research are:

- Demonstrated some of the potential uses of historical transactions data by non-asset backed 3PL companies to assess and mitigate risk
- Utilization of coefficient of variation, beta value and average month/month percentage change to measure volatility in linehaul rates
- Characterization of regions and lanes based on volatility
- Development of risk profiles for regions and individual lanes
- Utilization of historical linehaul rates distributions to price contracts
- Identification of factors such as agricultural activity and truck availability that influence the volatility in certain regions

6.4. Future Research

This research reveals many interesting opportunities for future work. For example:

- Incorporation of other external factors that might influence spot market rates volatility
- Identify other potential segmentation in terms of distance, regions, lanes, corridors, time periods (monthly vs. weekly), and others
- Investigation of connections between financial markets and linehaul spot price markets

- Combining data from more brokers and 3PL providers, and therefore adding more data to the analysis, would provide a more complete outlook of the market

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APPENDIX

Table 19: Top 10 risky long-haul lanes 2012 and 2013 (beta)

Lanes	OST	DST	Region	20122013Beta	20122013CV
303-397	GA	MS	Lower Atlantic	4.76	0.32
313-241	GA	VA	Lower Atlantic	3.20	0.30
300-272	GA	NC	Lower Atlantic	3.00	0.28
775-559	TX	MN	Gulf Coast	2.75	0.31
328-300	FL	GA	Lower Atlantic	2.68	0.40
463-410	IN	KY	Mid West	2.24	0.22
775-581	TX	ND	Gulf Coast	2.22	0.21
300-469	GA	IN	Lower Atlantic	2.15	0.30
852-902	AZ	CA	West Coast	2.07	0.29
295-604	SC	IL	Lower Atlantic	2.06	0.30

Table 20: Top 10 risky long-haul lanes 2012 and 2013 (coefficient of variation)

Lanes	OST	DST	Region	20122013CV	20122013Beta
320-395	FL	MS	Lower Atlantic	0.44	1.45
320-280	FL	NC	Lower Atlantic	0.44	1.63
320-303	FL	GA	Lower Atlantic	0.41	1.83
320-354	FL	AL	Lower Atlantic	0.40	1.13
328-300	FL	GA	Lower Atlantic	0.40	2.68
330-303	FL	GA	Lower Atlantic	0.39	1.07
320-300	FL	GA	Lower Atlantic	0.38	1.40
320-361	FL	AL	Lower Atlantic	0.37	1.37
336-303	FL	GA	Lower Atlantic	0.36	0.84
985-956	WA	CA	West Coast	0.36	0.19

Table 21: Top 10 risky long-haul lanes 2012 and 2013 (average monthly percentage change)

Lanes	OST	DST	Region	20122013AvgChange
303-397	GA	MS	Lower Atlantic	14.32%
302-386	GA	MS	Lower Atlantic	10.56%
295-604	SC	IL	Lower Atlantic	10.45%
775-559	TX	MN	Gulf Coast	8.43%
300-272	GA	NC	Lower Atlantic	7.83%
440-461	OH	IN	Mid West	7.77%
799-906	TX	CA	Gulf Coast	7.76%
070-281	NJ	NC	Central Atlantic	7.38%
480-461	MI	IN	Mid West	7.02%
463-410	IN	KY	Mid West	6.75%

Table 22: Top 10 risky short-haul lanes 2012 and 2013 (beta)

Lanes	OST	DST	Region	20122013Beta	20122013CV
604-604	IL	IL	Mid West	-14.02	0.82
601-601	IL	IL	Mid West	-13.44	1.36
917-917	CA	CA	West Coast	-6.68	0.52
477-461	IN	IN	Mid West	-6.20	0.59
287-272	NC	NC	Lower Atlantic	3.61	0.42
245-272	VA	NC	Lower Atlantic	3.22	0.38
467-452	IN	OH	Mid West	2.98	0.23
458-461	OH	IN	Mid West	2.94	0.43
750-762	TX	TX	Gulf Coast	2.71	0.48
917-900	CA	CA	West Coast	2.44	0.43

Table 23: Top 10 risky short-haul lanes 2012 and 2013 (coefficient of variation)

Lanes	OST	DST	Region	20122013CV	20122013Beta
601-601	IL	IL	Mid West	1.36	-13.44
604-604	IL	IL	Mid West	0.82	-14.02
281-272	NC	NC	Lower Atlantic	0.81	-0.01
477-461	IN	IN	Mid West	0.59	-6.20
917-917	CA	CA	West Coast	0.52	-6.68
750-762	TX	TX	Gulf Coast	0.48	2.71
917-900	CA	CA	West Coast	0.43	2.44
458-461	OH	IN	Mid West	0.43	2.94
287-272	NC	NC	Lower Atlantic	0.42	3.61
245-272	VA	NC	Lower Atlantic	0.38	3.22

Table 24: Top 10 risky short-haul lanes 2012 and 2013 (average monthly percentage change)

Lanes	OST	DST	Region	20122013AvgChange
604604	IL	IL	Mid West	138.91%
601601	IL	IL	Mid West	134.78%
477461	IN	IN	Mid West	54.43%
281272	NC	NC	Lower Atlantic	44.82%
917917	CA	CA	West Coast	35.84%
287272	NC	NC	Lower Atlantic	28.74%
902933	CA	CA	West Coast	23.48%
472461	IN	IN	Mid West	18.81%
088085	NJ	NJ	Central Atlantic	18.34%
600461	IL	IN	Mid West	15.63%

Table 25: Top 10 less risky long-haul lanes 2012 and 2013 (beta)

Lanes	OST	DST	Region	20122013Beta	20122013CV
040-226	ME	VA	New England	0.00	0.06
226-272	VA	NC	Lower Atlantic	0.00	0.21
936-924	CA	CA	West Coast	-0.01	0.10
753-708	TX	LA	Gulf Coast	-0.01	0.13
710-750	LA	TX	Gulf Coast	0.01	0.04
432-495	OH	MI	Mid West	0.01	0.12
442-531	OH	WI	Mid West	0.01	0.05
936-917	CA	CA	West Coast	-0.01	0.16
320-302	FL	GA	Lower Atlantic	-0.02	0.30
088-604	NJ	IL	Central Atlantic	-0.02	0.09

Table 26: Top 10 less risky long-haul lanes 2012 and 2013 (coefficient of variation)

Lanes	OST	DST	Region	20122013CV	20122013Beta
322-226	FL	VA	Lower Atlantic	0.02	-0.17
314-374	GA	TN	Lower Atlantic	0.02	-0.04
309-334	GA	FL	Lower Atlantic	0.03	0.07
535-785	WI	TX	Mid West	0.03	-0.04
072-140	NJ	NY	Central Atlantic	0.04	-0.04
710-750	LA	TX	Gulf Coast	0.04	0.01
072-601	NJ	IL	Central Atlantic	0.04	0.21
314-282	GA	NC	Lower Atlantic	0.04	0.58
072-608	NJ	IL	Central Atlantic	0.04	0.13
314-328	GA	FL	Lower Atlantic	0.04	0.26

Table 27: Top 10 less risky long-haul lanes 2012 and 2013 (average monthly percentage change)

Lanes	OST	DST	Region	20122013AvgChange
780799	TX	TX	Gulf Coast	0.01%
775641	TX	MO	Gulf Coast	0.02%
322226	FL	VA	Lower Atlantic	0.02%
314374	GA	TN	Lower Atlantic	0.02%
767785	TX	TX	Gulf Coast	0.03%
072601	NJ	IL	Central Atlantic	0.03%
314370	GA	TN	Lower Atlantic	0.03%
767799	TX	TX	Gulf Coast	0.04%
805741	CO	OK	Rocky Mountain	0.05%
072140	NJ	NY	Central Atlantic	0.06%

Table 28: Top 10 less risky short-haul lanes 2012 and 2013 (beta)

Lanes	OST	DST	Region	20122013Beta	20122013CV
178-226	PA	VA	Central Atlantic	0.00	0.01
229-226	VA	VA	Lower Atlantic	0.01	0.03
281-272	NC	NC	Lower Atlantic	-0.01	0.81
752-767	TX	TX	Gulf Coast	0.02	0.06
436-482	OH	MI	Mid West	-0.02	0.08
325-325	FL	FL	Lower Atlantic	-0.03	0.07
177-151	PA	PA	Central Atlantic	-0.06	0.14
175-226	PA	VA	Central Atlantic	-0.07	0.11
956-945	CA	CA	West Coast	-0.07	0.22
182-226	PA	VA	Central Atlantic	-0.08	0.07

Table 29: Top 10 less risky short-haul lanes 2012 and 2013 (coefficient of variation)

Lanes	OST	DST	Region	20122013CV	20122013Beta
178-226	PA	VA	Central Atlantic	0.01	0.00
720-638	AR	MO	Gulf Coast	0.02	-0.12
780-733	TX	TX	Gulf Coast	0.03	0.17
229-226	VA	VA	Lower Atlantic	0.03	0.01
072-190	NJ	PA	Central Atlantic	0.05	0.45
780-784	TX	TX	Gulf Coast	0.05	0.27
550-548	MN	WI	Mid West	0.05	0.08
170-226	PA	VA	Central Atlantic	0.06	-0.13
072-082	NJ	NJ	Central Atlantic	0.06	0.44
752-767	TX	TX	Gulf Coast	0.06	0.02

Table 30: Top 10 less risky long-haul lanes 2012 and 2013 (average monthly percentage change)

Lanes	OST	DST	Region	20122013AvgChange
923917	CA	CA	West Coast	0.00%
330328	FL	FL	Lower Atlantic	0.03%
780733	TX	TX	Gulf Coast	0.04%
780784	TX	TX	Gulf Coast	0.05%
720638	AR	MO	Gulf Coast	0.15%
436482	OH	MI	Mid West	0.15%
178226	PA	VA	Central Atlantic	0.17%
908933	CA	CA	West Coast	0.18%
072190	NJ	PA	Central Atlantic	0.18%
296272	SC	NC	Lower Atlantic	0.20%