

Multi-Stop Trucking: A Study on Cost and Carrier Acceptance

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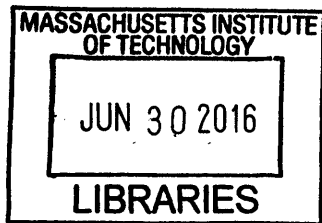
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ABSTRACT

Multi-stop truckload has been gaining importance in recent years as part of a shift away from Less-than-truckload freight. In our research, we sought to understand how the price and carrier behavior vary as the number of stops increases. Rational economic theory says that these shipments will be more expensive, and experience shows that in practice they also tend to get rejected more often. This thesis tested these two likely results together with other factors known for affecting price and rejection rates, such as lead time, clustering of the stops, etc. We used logistics regression to predict the acceptance ratio and ordinary least squares regression to model the price based on historical data. We found that there is an inherent cost associated with multi-stops, which depends on the number of stops and whether the stop is a pick or a drop. The proximity of these stops as well as the stop-off charge can also impact the price. Carrier acceptance and routing guide depth depends on the price structure and load characteristics. As the number of stops increases, it takes longer for a tender to be accepted and the shipment performance also deteriorates with an increased likelihood of late delivery- especially if the initial pickup is late. Therefore, companies need to be aware of the hidden costs associated with multi-stop truckloads as they plan their transportation network.

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- Xiaojia Chen, May 2016

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TABLE OF CONTENTS

Acknowledgements.....	3
1. Introduction	6
1.1 Thesis Organization	6
1.2 The Full Truckload (TL) Market in the US.....	7
1.3 The Shift towards Multi-Stop Truckloads.....	9
2. Literature Review.....	12
2.1 Vehicle Routing, Pricing and Scheduling	12
2.2 Economics of Order Acceptance and Pricing	14
2.3 Full Truckload Order Acceptance	15
2.4 Summary	18
3. Data Characterization	19
3.1 Data Source	19
3.2 Model Scope.....	19
3.3 Data Cleansing.....	20
3.4 Modeling Approach.....	22
3.5 Data profile.....	22
4. Multi-stop Carrier Behavior & Order Acceptance	30
4.1 Order Acceptance Model	30
4.2 Results from Logistic Regression.....	42
Out-of-Route Miles.....	43
Clustering.....	44
Continuous Move	44
Additional Stops.....	44
Line Haul and Stop-Off Charges.....	45
Origin and Destination Lanes.....	45
4.3 Summary	48
5. Multi-stop truckload Pricing	49
5.1 Data Analysis	49
Impact of Additional Stops	49
SOC and Line-haul.....	50

Planned vs. Unplanned	50
5.2 Pricing Model	51
5.3 Pricing Model result	54
Scenario Analysis	56
Additional Stops.....	57
Distance and Out-of-route miles	57
Market Index	58
Special Multi-stop Cases: Planned Loads and Continuous Moves	58
Lead Time.....	60
Regional Sensitivity.....	61
Stop-off Charges	63
5.4 Pricing and Routing Guide Depth	67
5.5 Summary	69
6. Conclusion	72
6.1 Management Insights.....	72
Optimizing the Routing Guide	73
6.2 Future Research	74
More Complete Datasets.....	74
System Bottlenecks and Little’s Law	76
Strategy Comparison	77
APPENDIX.....	78
I. Original Dataset Variables	78
II. Statistical Package Output	80
A1. Order Acceptance Model- Logistic Regression Output.....	80
A2. Pricing model – linear regression base model	83
References	90

1. INTRODUCTION

The trucking market is often said to be the lifeblood of the US economy, without which the economy would halt to a standstill. In the context of freight transportation, trucks are but one of a myriad of options also including rail, parcel, barge and intermodal. Trucking alone has a market value of \$681.7 billion and accounted for 81.2% of the United States' freight bill in 2013 (Corridore, 2014), underscoring its importance as a vital link in the supply chain that connects local and national businesses across the nation.

In an industry that has seen many changes since the start of deregulation with the Motor Carrier Act of 1980, shifting economic conditions, industry consolidation and disruptive new technologies mean that traditional paradigms can change without warning. Trucking is traditionally divided into Full Truckload (TL)¹ and Less-than-Truckload (LTL), which had revenues of \$298.12 billion and \$51.5 billion in 2012 respectively (Corridore, 2014). In recent years, a modality called Multi-Stop Truckload (MSTL) has gained in importance. While considered by many to be a variant of TL, it differs in some aspects from traditional TL.

This thesis aims to fill a gap in the understanding of multi-stop truckload by focusing on its impact on pricing and carrier behavior.

1.1 Thesis Organization

The organization of the thesis is structured as follows. Chapter 2 presents a review of the relevant literature, and discusses previous research that will later be built upon. This includes

¹ The term TL refers to the movement of cargo that is enough to fill an entire container, as opposed to LTL, which refers to shipments of smaller quantities (in which a container might contain goods from several shippers).

vehicle routing from carriers' perspective as well as shippers' strategies to increase tender acceptance while reducing the costs. Chapter 3 gives an overview of the methodology employed and dives into the data set, providing a descriptive analysis that compares MSTL with direct TL. Detailed modeling results and analyses are discussed in Chapter 4, a section devoted to carrier behavior, and in Chapter 5, which discusses the impact on pricing. Conclusions and insights into how this research can help carriers and shippers are found in Chapter 6. The appendix includes the full statistical package output of the analyses.

The rest of this chapter explains how the full truckload market in the US currently operates, together with some context about how Multi-Stop Truckload fits in.

1.2 The Full Truckload (TL) Market in the US

The TL market is characterized as highly fragmented, with a large number of small owner operators, which can make it difficult to coordinate shipments. In parallel, the industry has struggled with bouts of driver shortages, with many believing that currently there is a significant driver shortage upwards of 40,000 drivers (Costello and Suarez, 2015). Third-party logistics brokers help alleviate these issues by connecting companies desiring to ship freight (“shippers”) with the different carriers.

Companies that regularly need large amounts of products transported will often contract with transportation providers to secure lower prices. An alternative to contracts is the spot market, where freight is put up for bid, but is subject to more volatility and as a result can be less desirable. In the full truckload industry the prevalent type of contract is annual pricing that fixes the cost per mile for different lanes (lanes are usually defined as origin city and destination city

pairs), together with a schedule of additional charges known as “accessorials”. Accessorials are fundamentally designed to compensate drivers for their time, and range from detention charges, applied when a truck’s dwell time at a stop exceeds the allotted 2-hour window per stop, to stop-off charges, which are applied to additional stops.

While contracts remove some of the uncertainty in freight transportation costs, uncertainty is never completely removed because contracted carriers are not *obligated* to accept all the loads offered by the shipper. If contract carriers accept a tender, they must do so at the contracted rate, but if they don’t possess enough capacity to do so or find it unprofitable they can reject the tender. Sporadic lack of capacity is not uncommon in a market characterized by a relatively inflexible supply of trucks and drivers, highly seasonal demand and tenders with short lead times.

As a result, companies contract with multiple carriers to ensure that their loads are transported by at least one carrier. The contracting process is done through a bidding process by having transportation providers bid on selected lanes, often through a combinatorial auction. This is typically done every year to avoid having the rates become “stale” as a result of market changes.

The results of the bids and contracts help companies organize their carriers by priority (usually by cost) for every lane in what is known as a “routing guide”. Whenever shippers need something transported, they initialize a “tender sequence”. During the tender sequence, they tender their load to their preferred carrier: if the carrier rejects the load, the tender is then passed along to the next preferred carrier in the routing guide. A tender sequence ends when a

carrier, possibly further down the routing guide, eventually accepts the load. The number of carriers a load is tendered to before it is accepted is referred to as the routing guide depth, and is an indicator of the acceptance rate. For example, a routing guide depth of 1 means the load is accepted by the primary or preferred carrier. In the cases where no carrier in the routing guide accepts, this load is then moved to the spot market and is opened for bids.

1.3 The Shift towards Multi-Stop Truckloads

Shippers have traditionally used LTL when moving smaller volumes that do not warrant a full truck. LTL, unlike TL, pools shipments from multiple shippers onto a single freight truck to aggregate economies of scale and usually results in cheaper shipments, especially for freight weighing between 150 and 12,000 lbs. Although LTL can provide cost flexibility for smaller shipments, the tradeoff is longer transit time and higher unreliability due to an increased number of claims related to damages and late delivery. Due to the amount of handling that takes place, LTL typically slows down the delivery process and increases the risk of damage. One alternative to LTL, multi-stop truckload (MSTL), consists of using one full truckload to deliver to multiple stops. MSTL has been gaining traction in recent years as transportation managers seek to balance LTL's higher unreliability while utilizing their trucks' capacity to the fullest.

MSTL in the United States is priced using the annual contract pricing structure of TL, meaning that the rates per mile for MSTL are the same as those for regular TL for the same initial origin and final destination city pairs. The only difference lies in the "stop-off charges" (SOC), which are part of the aforementioned accessorial costs charged for stops in addition to the origin and destination rate (also known as line haul). Stop-off charges are agreed upon between shipper

and carrier in the contracting process together with the other accessorial costs. Because the rise of MSTL is relatively recent, the frequency of MSTL in a lane is not usually known with certainty when the contract is negotiated and as a result, a question remains as to whether it is priced correctly.

Some countries outside the US, such as those in Europe, use contracts designed exclusively for MSTL. To do this successfully, shippers must plan their MSTL routes ahead of time and communicate them to carriers during the procurement process. These exclusive contracts don't allow as much flexibility to add or change stops, and as a result have been a bit slower in gaining acceptance in the US. At the same time, some shippers in the US have started including information about MSTL during their contract negotiations with carriers, and MSTL-only routes might become more common in the US in the future.

Although MSTL has potential advantages over both traditional truckload and LTL, and is already considered a different variant of transportation by carriers and brokers alike, few studies have examined its associated potential benefits and hidden costs. While there are clear situations where multi-stop truckload can be the best option, there are also cases where the best mode choice is not apparent. When building a multi-stop truckload, shippers need to consider the following possibilities beyond cost savings: products on the same truck need to be compatible (consider the case of having both chemicals and food), delivery time may be impacted due to multiple drop-offs and pick-ups, out-of-route miles (miles beyond origin and destination, for intermediate stops) may be incurred, stop-off charges may apply, and the load may be rejected by their preferred carrier simply because drivers are not trained to handle these loads. Carriers need to take into account the human and coordination factors involved in multi-stop and re-

evaluate the costs and opportunity costs. Our thesis aims to explore MSTL in the context of the US and answer the question of how having multiple stops impacts price and carrier behavior.

2. LITERATURE REVIEW

In accordance with trucking's outsize influence in transportation costs there is also a large body of research on how to properly allocate resources to ensure timely delivery of products. In this section we go over past papers that deal with general pricing models as well as pricing in the context of trucking.

2.1 Vehicle Routing, Pricing and Scheduling

There is extensive academic and industry research on the factors affecting route pricing.

Arunapuram, Mathur and Solow (2003) summarized carriers' major concern as follows: how to optimize vehicle routes and scheduling so as to minimize costs (and maximize profits) in the face of complexity and uncertainty. Carriers must be judicious in how they price their offerings as they possess limited fleets but also have to offer a multitude of shipping options (using refrigerated or dry vans and following shippers' strict delivery rules and procedures while maintaining narrow delivery windows). Accepting the wrong shipments can end up costing carriers money if, for example, their trucks run empty (such as "empty miles" in their "backhaul").

This problem, known as the Vehicle Routing Problem (VRP), has been studied widely. Laporte (1991) mentions that due to the many variations of the problem, exact solutions are often superseded by heuristics. In practice, many carriers adopt a mix of exact solutions and heuristics. Many Transportation Management Systems (TMS) can provide solutions to the VRP using these approaches. To deal with the various different shipping options, carriers have added increasingly arcane rules to their pricing structure.

One big cost component for carriers is fuel cost. To deal with fuel volatility, cost sharing agreements between carriers and shippers have become the norm. The cost sharing is done through a mutually agreed upon fuel surcharge schedule that compensates one party for fluctuations from the baseline using an index published daily by the US Energy Index Association (EIA). This type of risk-sharing is not without complications, as the exact cost-sharing proportion can vary from carrier to carrier, but is considered standard in the industry.

In trucking, the direction of a haul is extremely important and shippers can often leverage carriers' existing networks so that "deadhead" miles (empty miles on return trips) decrease, sharing the profits between shipper and carrier (Caplice and Sheffi, 2003). For example, if a carrier has a lot of volume from A to B but few from B to A, the shipper can offer the carrier loads from B to A. In this case, the shipper helps the carrier to reduce empty miles going from B to A and synergy will be achieved.

A related way to create synergy between a load and a carrier's network is through lane aggregation. Collins and Quinlan (2010) investigated the impact of bidding aggregation on truckload rates. Using regression, they developed a model that showed that bundling lanes can provide significant savings for shippers due to economies of aggregation. Their thesis provides a solution to low-volume lanes that often require shippers to pay premiums since carriers may risk driving back empty. They proposed a model in which shippers can bundle lanes by defining larger origin and destination areas. The recent industry proclivity towards multiple stops threatens to complicate the equation as it raises questions as to how the areas should be drawn and how the lanes should be bundled.

2.2 Economics of Order Acceptance and Pricing

Agency theory in economics, which studies relationships between parties, can shed some light into many aspects of the trucking market. In general, it states that any time there is an incentive mismatch between two parties there will exist some inefficiencies. Milgrom and Roberts (1992) famously posited that the high percentage of owner operators in long-haul trucking compared to short haul was a result of incentive alignment to improve efficiency: by owning their trucks, drivers were incentivized to take better care of them. Had they not, they might have engaged in behavior that was not so good for the truck- effects which would have been magnified and harder to monitor in long hauls.

In the context of the TL market, long-run and short-run incentive mismatches can also explain why the contract commonly used in TL does not guarantee shipping capacity. In the language of economics, carrier contracts in TL can be thought of as a mixture of a “formal contract” where some terms are spelled out clearly (such as the line haul price, accessorials) and a “relational contract” relying on unspoken agreements (“I will accept X% of your loads”). While it is true that in the long run it is in contract carriers’ interests to accept as many tenders as possible to ensure they are contracted again next year, once yearly contracts have been agreed upon carriers can succumb to short-term temptations to not honor them. This can manifest itself in carriers preferring to offer their capacity in the spot market when they can obtain higher prices there.

In multi-stop trucking, this problem is potentially exacerbated because it can mean extra costs for carriers beyond what the stop-off charges compensate for. One implication is that shippers

and carriers might benefit from moving towards more formal contracts such as those used in Europe, or communicate better and design a better incentive scheme to prevent such behavior.

Another economic theory that help explain behavior in the trucking market is that of matching theory², which deals with resource allocation in instances where changing the price is not possible. Lu and Lariviere (2012) studied capacity allocation mechanisms used by suppliers to determine how much capacity to give to each of its customers when demand exceeds supply. “Turn-and-earn”, where suppliers allocate capacity based on previous order quantities, arose as viable strategy, among other possible equilibrium strategies. In trucking, this might imply that carriers are using similar allocation mechanisms during periods of excess demand by shippers, and that shippers might do well to consider other factors besides price to increase their “capacity allocation” of shipping services (and in turn their tender acceptances)- particularly when price cannot be adjusted.

2.3 Full Truckload Order Acceptance

Extensive studies and white papers have examined factors that affect shipment acceptance and pricing, particularly in the context of TL.

According to Caldwell and Fisher (2008), getting load tenders rejected by multiple carriers can increase the cost of transportation. Since shippers normally place the cheaper carriers as their preferred carriers, the deeper the shipper has to go into the routing guide, the higher the rate per mile they will have to pay. Caldwell and Fisher (2008) observed an increase of \$0.06 per mile for each increase in routing guide sequence, or a 7.9% increase in the initial rejection

² Economists who pioneered matching theory won the Nobel Memorial Prize in Economic Sciences in 2010

followed by 3.2% in subsequent rejections. To find out the reasons shipments get rejected, Kim (2013) conducted regression analysis and observed that volatility of volume on each lane partially explains tender rejection, especially for short hauls mostly hauled by regional carriers. Kafarski and Caruso (2012) interviewed many carriers and concluded that most carriers reject shipments because of short lead time, long dwell time, inconsistent volume and low price. Kim (2013) found that paying more than the market rate does not effectively reduce rejection. Therefore, a few strategies that shippers can potentially deploy include increasing the lead time, reducing the dwell time, and being more consistent in terms of volume.

Lead time refers to how far ahead carriers were notified of a possible shipment. When Caldwell and Fisher (2008) researched factors affecting order acceptance, advance notice or lead time was the most significant factor in order acceptance: orders that gave carriers more time to plan their vehicle routing resulted in higher acceptances. Other significant factors found included the day of the week and the locations involved in the route, suggesting seasonality and regional sensitivities. Caldwell and Fisher (2008) suggested that shippers re-evaluate their business policies to account for lead time and other critical factors such as seasonality that can impact tender acceptance and cost.

For multi-stop truckload, the biggest challenge is the risk of increased dwell or detention time (which refers to the time it takes to unload and load at each stop). When the number of stops increases, the dwell time increases; therefore, any delay along the process can be amplified.

Under current regulation, truck drivers may not drive after 60/70 hours on duty in 7/8 consecutive days (Federal Motor Carrier Safety Administration, 2016). By increasing dwell time, drivers' available driving time is reduced. 80% of drivers reported that dwell time affected their

productivity (Leigh, 2014). Therefore, shippers need to reduce dwell time in order to create efficiency for carriers. Shippers can do so by implementing an appointment scheduling system to avoid backlogs of vehicles at loading docks (CHR White Paper, 2013).

Amiryan and Bhattacharya (2015) suggests that another way to reduce cost is to increase lane loyalty or consistency to a carrier. Loyalty is defined as the number of weeks a carrier receives a tender from the shipper divided by the total number of weeks a shipper offers loads in this lane. The paper concluded that shippers can benefit from lower pricing offered by the carriers by consistently offering a carrier loads on a lane for 30 to 35 weeks a year.

Besides changing lead time and dwell time and increasing loyalty, shippers can also focus on other strategies to make their freight more attractive, such as avoiding poorly secured freight, combining drop trailer and live loading, understanding fuel surcharges, and making payment on time (CHR White Paper, 2013).

As shippers look for ways to decrease transportation cost, they must also be aware of trade-offs. One of the major trade-offs is performance: in a study of price and on-time performance, Amiryan and Bhattacharya (2015) indicated that cost per load starts to decrease as OTD (On-Time Delivery) performance deteriorates, but the relationship only holds when OTD is less than 80%. On the contrary, OTP (On-Time Pickup) is not as relevant in determining the price since there is 80% probability that a carrier will deliver on time even if the shipment is picked up late. We are curious to see whether the relationship holds for multi-stop truckload.

2.4 Summary

Having multiple stops along the way adds another layer of complexity for both carriers and shippers. Carriers need to reassess guidelines for accepting or rejecting loads and redesign the pricing model. Shippers must align with carriers in order to obtain favorable pricing. Shippers can reduce transportation cost by altering lead time and dwell time while helping decrease carriers' inefficiencies. At the same time, shippers also need to be aware of the trade-off between pricing and performance.

3. DATA CHARACTERIZATION

In this section we provide an overview of the models and methods employed to analyze multi-stop truckload freight. We will also provide descriptive analysis of the datasets to gather insights as to *what* MSTL looks like, *who carries* MSTL, *where* MSTL is prevalent, and the *performance* of MSTL.

3.1 Data Source

The source of our data was TMC, a division of 3rd party logistics company CH Robinson which provides Managed TMS Services for companies looking to outsource the tactical execution but still looking to retain the contractual control and relationships directly with carriers. Unique to TMC is the fact that while they are a division of CH Robinson, they are carrier agnostic and tender loads to multiple carriers in accordance to the companies they are serving - as opposed to tendering to just CH Robinson. Two datasets were provided over the 2013-2015 period: the first contained tender records over the 2.5 year time period, the second had detailed stop information for all shipments actually carried out. The datasets included 5.6 million tender records and information for 400,000 shipments (encompassing 500,000 stops), which included records from over 4,000 carriers and 190 shippers.

For an exact description of all the fields included in the dataset, including example entries, refer to the Appendix.

3.2 Model Scope

The scope of the data analyzed was limited to make sure all the tenders and loads were comparable to each other in terms of pricing and acceptance. Shipments originating or ending

outside the continental US, including places like Canada, Mexico and Alaska were excluded from the data owing to different market dynamics and inter-border regulations.

We limited the data to "dry van" TL loads over 250 miles. Refrigerated trucks (or "reefers") are an alternative to dry vans, but have a higher cost due to their refrigeration equipment, and as such are used only when requested by customers. They are subject to different supply and demand patterns. Similarly, short hauls of less than 250 miles usually follow regional patterns that might not be generalizable to the whole US, and so were excluded.

Missing information in the dataset such as detailed breakdowns of detention charges and distance information between stops limited the analysis performed. Similarly, the stop level dataset and the tender level dataset didn't have exact 1 to 1 correspondence. This meant that not all of the accepted tenders in the tender dataset had stop level information, and not all of the stops in the stop level dataset had tender information about them.

For example, there were 3.7 million tenders accepted in the tender information, of which 180,079 were multi-stop. The stop-level dataset (which by definition only included multi-stop loads) only had data for 137,432 of these.

3.3 Data Cleansing

The outliers identified were:

- Loads with more than 10 stops.
 - After talking to TMC, we decided to exclude loads with more than 10 stops (5 picks or 5 drops), as those are not representative of normal tenders. In most

cases, they get accepted almost immediately due to pre-agreements between shippers and carriers.

- Direct hauls that have stop-off charges. These only occur in special cases, and as such were also excluded from our analysis.

Other data points appeared to be outliers at first, such as loads had to be tendered over 30 times to different carriers before being accepted. However, this was found to be actually the case and as such the data was kept.

In the end, we excluded data with the following criteria:

- Modes other than Truckload
- Length of hauls < 250 miles
- Modes other than dry van
- Number of pickup stops or drop-off stops > 5
 - This was mostly due to the sample size for these not being significant, with < 1000 data points
- Rate per Mile < \$0.7 or Rate per Mile > \$3.5
 - This encompassed less than 0.05% of the data. Such rates were usually due to one-off special circumstances.
- Direct haul with Stop-off Charges > 0
 - Stop-off charges are usually only applied to multi-stop loads. The presence of direct hauls with stop-off charges is rare and more likely than not due to a data entry error.

- Loads originating or arriving at destinations outside the continental US
- Loads that are automatically accepted (without a tendered date)
- Lead Time more than 200 days
- Entries missing dates or with impossible future dates

3.4 Modeling Approach

To determine the effect of multiple stops we developed models for both carrier behavior and pricing. To model carrier behavior we focused on order acceptance using a supervised classification algorithm known as logistic regression. To model pricing, we employed linear regression to understand how having multiple stops affects the price of a load. The assumptions made in our models include:

- We ignore carrier-specific capacity constraints that may arise due to carrier size or specialization.
- To model carrier behavior in order acceptance, we only included the things that carriers can see at the time of decision-making, such as origin, destination, number of stops, etc.

These two models underpin and form the basis of the thesis.

3.5 Data profile

3.5.1 Multi-Stop Frequency

From the dataset, we observed that MSTL has gained popularity over the past three years. The number of multi-stop truckloads has trended upward, from 6.42% of the total business in 2013 to 7.39% in 2015.

The data profile in Table 1 shows that the majority of the loads (96%) are regular 2-stop direct TL shipments (1 pickup and 1 drop with no intermediate stops).

Table 1. Frequency of loads by number of stops. Red coloring indicates scarceness

		Drop		
		1	2	3
Pick	1	3,545,326	78,479	37,679
	2	10,155	12,487	1,466
	3	1,362	186	150

The majority of the MSTLs were picked up from one location and dropped off at 2 or 3 locations. It is relatively rare for loads to be picked up from multiple locations - there were more loads with numerous drops than loads with numerous picks. We suspect that whether multiple stops occur at pickups or drops may affect load acceptance and cost; therefore in our model, these are treated differently. Note the cells highlighted in red: due to lack of records, tenders with 3 picks may not constitute a significant sample size.

3.5.2 Length of Haul

In general, MSTL was more commonly observed for long haul shipments. For direct loads, loads below 750 miles account for more than 60% of the freight volume, whereas they only represent 40% of multi-stop loads. Direct TL have a higher concentration of shorter hauls while MSTL are more spread across the spectrum. Because shippers normally pay a fixed fee for MSTL, they perceive longer hauls as more economically beneficial, since longer hauls tend to have lower contracted rates per mile.

Table 2 shows that 3-stop loads are most prevalent among hauls with shorter lengths. As the distance increases, the proportion of 3-stop or 4-stop loads decreases in favor of 5-stop or 6-stop loads. In the 3000 – 3500 mile range, more than 60% of the MSTLs have 5 or 6 stops.

Table 2. Average haul length by number of stops

Total Stops	Miles (bin)						
	250 - 500	500 - 1000	1000 - 1500	1500 - 2000	2000 - 2500	2500 - 3000	3000 - 3500
3	67%	47%	40%	42%	43%	28%	9%
4	25%	34%	31%	35%	30%	39%	26%
5	7%	12%	17%	13%	17%	23%	38%
6	1%	6%	13%	10%	10%	9%	26%

3.5.3 Carrier Summary

Our dataset confirms the perception that the truckload market is very fragmented. Out of 4000+ carriers represented, only 733 of them haul MSTL. Table 3 shows that Carrier 1 hauls 10% of the multi-stop freight, making it the biggest broker in terms of freight volume. The top 75 players haul 80% of multi-stop freight, but they exhibit different behaviors when it comes to acceptance ratio (percentage of the loads that are accepted). Some carriers such as carrier 1 accept almost all the tenders. Other carriers such as carrier 5 accept less than half of their MSTL tenders. This could be due to capacity constraints and lack of driver training to haul multi-stop loads. In general, carriers are more likely to accept the load if it is tendered to them first.

Table 3. Summary of the Top 10 MSTL Carriers

TOP 10 Carriers	Loads Accepted	Loads Tendered	% Accepted	% 1ST Accepted	Type
<i>Carrier 1</i>	19,714	24,522	80%	91%	Broker
<i>Carrier 2</i>	8,221	8,339	99%	99%	Asset based
<i>Carrier 3</i>	6,931	7,111	97%	99%	Asset Based
<i>Carrier 4</i>	4,205	4,327	97%	99%	Asset Based
<i>Carrier 5</i>	3,426	7,316	47%	73%	Asset Based
<i>Carrier 6</i>	2,734	3,045	90%	#N/A	Asset based
<i>Carrier 7</i>	2,579	2,594	99%	100%	Broker
<i>Carrier 8</i>	2,402	2,573	93%	97%	Asset based
<i>Carrier 9</i>	2,376	3,887	61%	97%	Broker
<i>Carrier 10</i>	2,222	2,738	81%	95%	Asset based

Categorizing the 75 carriers as asset based or broker, we looked at acceptance ratio and the percentage of hauls that are MSTL. In Table 4 we found that asset-based carriers accept fewer multi-stop loads (64% of the tenders are accepted, as opposed to 75% accepted by brokers) but multi-stop loads are bigger portion of their business (16% compared to 8% for brokers). One possible explanation for this is a commonly held perception that asset-based carriers are more reliable with higher degrees of accountability: this leads to customers placing them higher up in routing guides and giving them more tender opportunities. However, they are pickier when it comes to accepting tenders.

Table 4. Comparison between Asset Based Carriers and Brokers

	Accepted	Tendered	% Accepted	% 1ST Accepted	Multi-stop %	Carrier Count
Asset based	89,524	138,801	64%	85%	16%	60
<i>Big</i>	44,366	64,652	69%	87%	11%	24
<i>Medium</i>	15,611	27,270	57%	79%	22%	13
<i>Small</i>	24,363	40,034	61%	81%	31%	22
Broker	39,709	53,207	75%	92%	8%	14

For asset based carriers, we further looked into the impact of fleet size on load acceptance. According to the industry norm, companies with more than 500 trucks were classified as big carriers, companies with 200 – 500 trucks as medium carriers and companies with less than 200 trucks as small carriers. The results show that big carriers are more likely to accept MSTL than medium or small carriers, but MSTLs are a smaller portion of their business (11% of their business compared to 30% for small carriers). Interestingly, medium sized carriers are the least likely to accept MSTL tenders. This may be because big carriers have the capacity to accept the loads. Similarly, small regional carriers have often been observed to specialize in specific niches such as multi-stop to the point where it is a big portion of their business. At the same time, there may be a large degree of self-selection in the dataset, with only small carriers willing to fill niches such as multi-stop being included in routing guides by shippers.

3.5.4 Lane breakdown

We selected the top lanes (city to city) for multi-stop loads in terms of volumes and compared the cost and routing guide depth for multi-stop and direct. The results are shown in Figure 1.

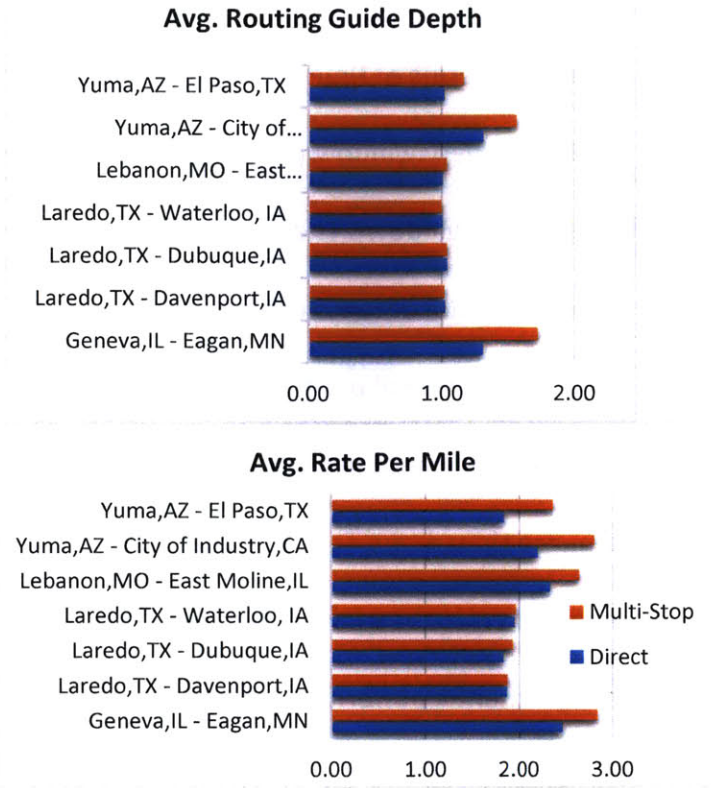


Figure 1. Average Routing Guide Depth and Rates per Mile for Direct and Multi-Stop

For all of the top lanes, MSTL on average exhibits a higher rate per mile. The cost difference for some lanes is more significant than for others. In terms of routing guide depth, most of the multi-stop loads go deeper in the routing guide. The three lanes originating from Laredo exhibit similar cost structure for both multi-stop and direct and with almost no difference in routing guide depth. However, for other lanes such as those originating from Yuma, multi-stop loads cost a lot more than direct loads per mile. The difference in routing guide depth is also very significant. Therefore, we suspect that there is a positive relationship between the routing guide depth and the premium the shipper has to pay- and that on average, MSTL are more expensive and have higher routing guide depth than direct TL.

3.5.5 On-Time Delivery

OTD (On-time Delivery) measures carriers' performance in terms of timeliness. As defined in our data, on-time deliver refers to carriers meeting the delivery window (by the minute if that is specified, or by the day if there is no specified delivery time window). The research by Amiryani and Bhattacharya (2015) defined OTDPercent as the proportion of loads delivered on time relative to all the loads handled by the carrier. In this paper, we will use the same metric – OTDPercent measured at the last stop - to explore the performance implication for MSTL. In general, we observed that MSTL has worse performance than direct TL, but it does not deteriorate as more stops are included. The same research (2015) showed that 80% of late TL pickups still arrive on time, implying that shippers implement a buffer for direct TL.

Figure 2 in our dataset showed a similar percentage for late pickups delivered on time at 80%. For multi-stops, however, the percentage delivered on time if the load is picked up late deteriorates with the number of stops. That is, the more stops you have, the less likely you will be able to recover from the initial late pickup.

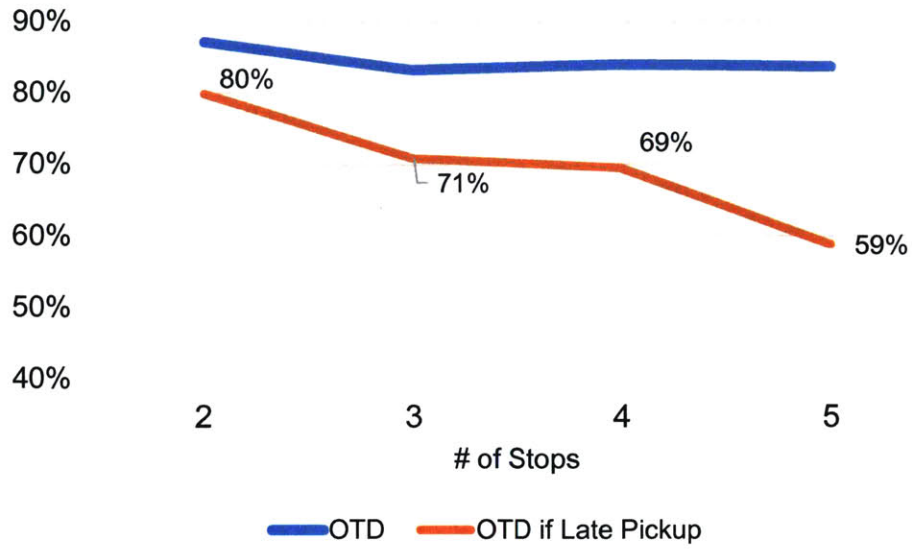


Figure 2. On-Time Delivery performance by number of stops. 2 stops is direct (1 pick 1 drop)

4. MULTI-STOP CARRIER BEHAVIOR & ORDER ACCEPTANCE

In this chapter, we seek to understand how having multiple stops in a load changes carrier behavior in terms of order acceptance. Do multi-stop loads have lower tender acceptance and thus higher routing guide depth? What are some of the factors that drive acceptance? Is it the number of stops or is it the pricing structure? We explore factors that may impact the routing guide depth through data visualization and then rigorously analyze these factors using logistic regression to model order acceptance.

4.1 Order Acceptance Model

When faced with a tender from a shipper, carriers have to decide whether to accept it or not. Mathematically, the carriers' decision can be modeled by a function that classifies tenders given their characteristics (lead time, number of stops, etc.) into two classes: ACCEPT or REJECT. We used the millions of tender records in our dataset, which provided examples of carriers' revealed preferences, to create a model for order acceptance.

While there are many classification techniques available, the main technique we used was logistic regression because of its ease of interpretation. Logistic regression allowed us to clearly see which factors affect the classification decision as well as their individual significance; other methods such as neural nets or Naïve Bayes, while possibly more predictive, are unable to do so. Furthermore, the output from logistic regression yields coefficient estimates that can be used to quantify the magnitude of each variable's effect on tender acceptance and yield insights into carrier behavior.

$$\log\left(\frac{P}{1+P}\right) = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_k * x_k$$

The logistic model formulation above, where P is the probability of tender acceptance, maps the natural logarithm of the *odds of acceptance* $\frac{P}{1+P}$ to a linear function of the tender characteristics x_1 to x_k . Once the coefficients β_0 to β_k are obtained, one can easily compute the probability of future tenders being accepted/rejected by plugging them into the logistic response function given by

$$P = \frac{e^{\beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_k * x_k}}{1 + e^{\beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_k * x_k}}$$

Note that the above formula yields a probability between 0% and 100%. In our thesis, we assumed that 50% is the cut-off³, marking the difference between acceptance and rejection, above which everything is accepted.

Model evaluation

To evaluate the order acceptance model, we used the McFadden's pseudo R². McFadden's pseudo R² provides a measure of the model fit in logistic regression; according to McFadden (1973) a pseudo R² number between 0.2 and 0.4 is considered a "good fit". The significance of each individual factor was assessed using p-values. A factor was deemed significant when it exceeded the 99% confidence level.

³ Depending on the level of confidence we want, as well as the cost of misclassification, we would usually set anything above 50% as more likely than not to be accepted.

The Impact of Additional Stops

Routing guide depth is a proxy of the attractiveness of a tender: a routing guide depth of 1 means the tender is accepted by the first carrier. The higher the routing guide depth, the more rejections occurred, and the lower the acceptance rate (and attractiveness of the load).

Table 5 shows a breakdown of routing guide depth by number of drops and picks (1 pick 1 drop is the direct TL scenario). We observe that in most cases, as number of drops go up, the routing guide depth also goes up. The routing guide depth is especially high with the 2 pick 3 drop and 3 pick 3 drop scenario. The relationship is less clear in number of picks, which may be due to a lack of records in scenarios with multiple pickups.

Table 5. Routing Guide Depth depending on number of Picks and Drops

Route Guide Depth		Drop		
		1	2	3
Pick	1	2.09	2.6	2.03
	2	1.94	2.4	2.77
	3	1.79	2.03	2.75

Nevertheless, we make the following hypothesis:

Hypothesis 1 (a): the more additional stops, the lower the acceptance.

Hypothesis 1 (c): The impact of additional stops on acceptance will differ depending on whether it is a pick or a drop.

To understand the impact of multiple stops on the tender acceptance in the logistic regression model, we looked at *additional* drops and picks. MSTL by definition will have additional drops and picks. We created dummy variables for additional 1, 2 and 3(+) drops or picks.

Out-of-route Miles

For multi-stop loads, the total miles driven is almost always higher than the distance from origin to destination, because in most cases, the driver needs to drive extra miles to intermediate stops. Therefore, we want to know if the out-of-route miles, the extra distance driven, will impact the cost and acceptance of a load. The out-of-route (OOR) miles is defined as below.

$$\text{OOR miles} = \text{total miles} - \text{distance from origin to destination.}$$

The total miles is given in our dataset. The direct distance from origin to destination is a straight line distance calculated using an equation given the latitude and longitude of the origin and destination.

An analysis of the distribution of Out-of-Route miles (as a percentage of the total distance travelled) in Figure 3, showed that it is very rare for multi-stop loads not to have any out-of-route miles. The majority of MSTL had 10 – 30% of the total miles driven being out-of-route miles.

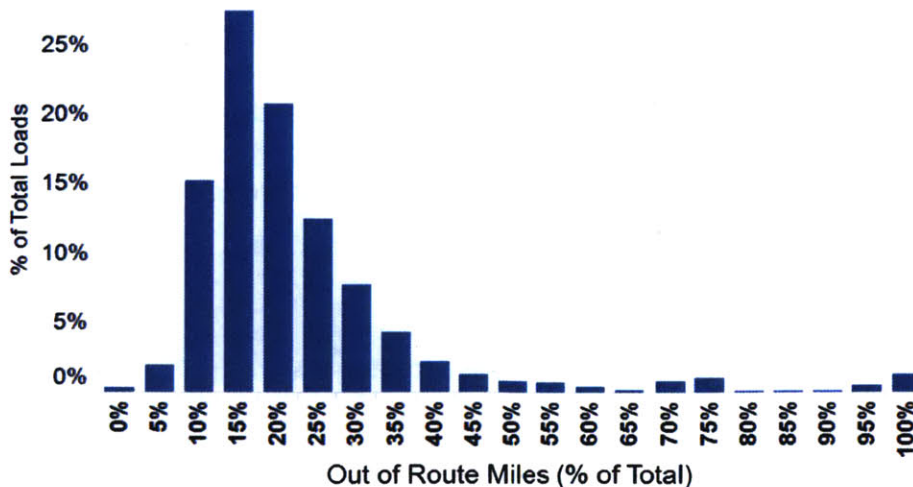


Figure 3. Distribution of Out of Route Mile Frequency

We hypothesize that routes with more out-of-route miles will incur more rejections because they deviate from the origin-destination city pair for which the rate was originally contracted. Carriers might feel they are being deceived: in an extreme case, a multi-stop route with many out-of-route miles might overlap with an existing contracted lanes for which rates are higher (while paying a lower rate).

Hypothesis 2 (a): the more out-of-route miles, the lower the acceptance rate.

Hypothesis 2 (b): the more the out-of-route miles, the higher the price.

Market index

The market index is a variable that shows the demand for trucking in each week. We suspect that the higher the weekly demand, the higher the price paid and the lower the carrier acceptance. While many trucking indices are available, including the DAT Rate per mile Index and the Morgan Stanley Freight Index (Bignell, 2013), we chose the Cass Truckload Line-haul Index because it was free and available online. The Cass Truckload Line-haul Index is a measure of market fluctuations in per-mile truckload line-haul rates, independent of additional cost components such as fuel and accessorials. In the 2006-2015 period, it fluctuated between values of 100 and 130. A high index means that the demand for TL is high and carriers' capacity is fully utilized. We hypothesize that when the index is high there will be more rejections and a higher price due to a supply and demand mismatch.

Hypothesis 3 (a): the higher the market index, the lower the acceptance.

Hypothesis 3 (b): the higher the market index, the higher the price.

Continuous move

Continuous move refers to instances where the truck drops off a shipment at one location and later returns to the same location to drop off or pick something up. A commonly employed strategy is for trucks to return to their origin location at the end of their route as their final drop. Another example is a pick-drop & pick-drop move, where the second stop serves as both a drop point and a pick point. Figure 4 depicts these two types of continuous moves.

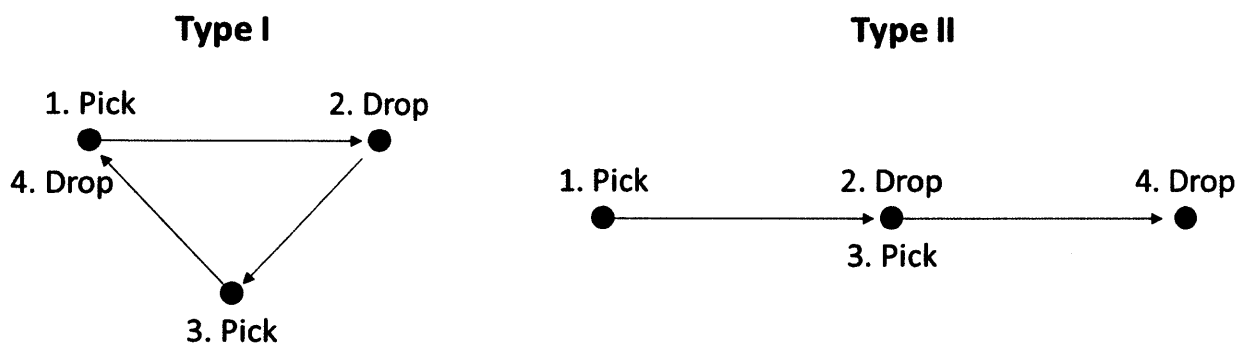


Figure 4. Example of the two types of continuous moves

These special type of multi-stop loads effectively reduce empty miles. As a result, it seems logical that continuous moves and regular multi-stop loads will be treated and priced more favorably.

Hypothesis 4 (a): continuous moves have a higher acceptance.

Hypothesis 4 (b): continuous moves have a lower price.

In our model, every stop, including intermediate stop, is coded as a pick or drop. We identified all loads with at least two stops at the same location and flagged them as continuous moves.

Clustering: Legs less than 30 miles apart

Another factor that we include in our model is a cluster indicator, to find out if the separation between stops has an impact on acceptance and price. That is, if many of the intermediate stops are clustered together, will the load attractiveness be higher than if the stops are scattered? We assume so because loads that are more clustered have fewer out-of-route miles.

Hypothesis 5 (a): Loads with clustered stops have a higher acceptance.

Hypothesis 5 (b): Loads with clustered stops have a lower price.

Hypothesis 5 (c): The impact of clustered stops on acceptance and price will differ depending on whether it is a pick or a drop.

Our dataset included distance information for the whole trip, but lacked information about distance between the stops. Distance between stops was approximated using the great circle equation⁴, which is reasonably accurate for the northern hemisphere to +/-10%. Thirty miles was picked as the cut-off distance for a “cluster”, being the length of a square with an area of 900 square miles as shown in Figure 5 (the average US county size is 997 square miles).

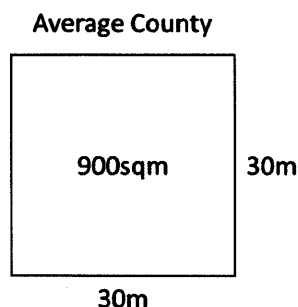


Figure 5. Representative average county size

⁴ The Great Circle distance $d = \text{acos}(\sin(\text{lat1}) * \sin(\text{lat2}) + \cos(\text{lat1}) * \cos(\text{lat2}) * \cos(\text{lon1} - \text{lon2}))$, where $(\text{lat1}, \text{lon1})$ and $(\text{lat2}, \text{lon2})$ are the coordinates for two different points

Two measures of clustering were derived: "Consecutive Picks < 30 miles apart" and "Consecutive Drops < 30 miles apart". The first, "Consecutive Picks < 30 miles apart," measured how many consecutive picks were located less than 30 miles apart from each other. The second one, "Consecutive Drops < 30 miles apart," measured how many consecutive drops were located less than 30 miles apart from each other.

Stop-off Charges

Shippers pay a fixed accessorial fee for MSTL known as the SOC (stop-off charge). To understand how much SOC shippers normally pay for multi-stop loads, we plotted the stop-off charge with number of stops in Figure 6.

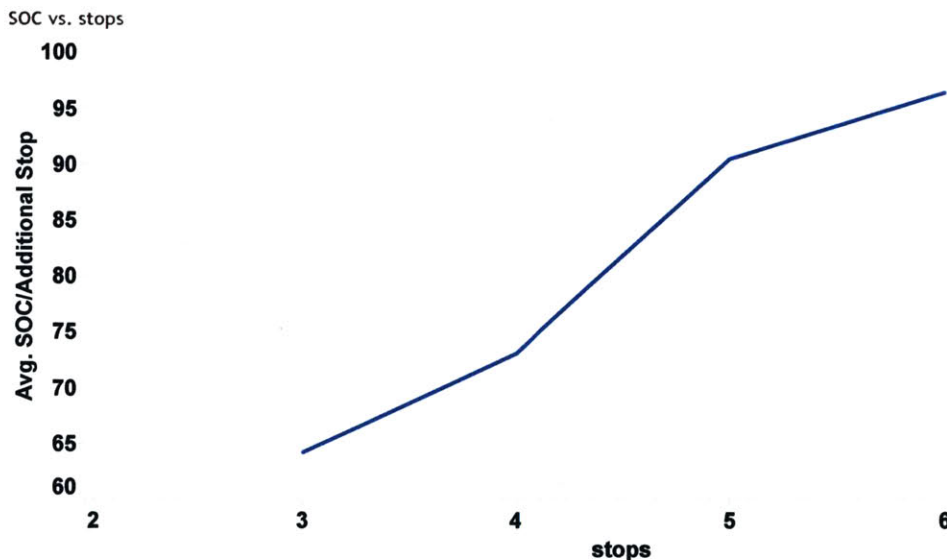


Figure 6. Average stop-off-charge per additional stop by number of stops

As the number of stops increases, the stop-off charge per additional stop also increases. When the shipper adds one additional stop (3-stop load), they pay on average of \$65 for SOC.

However, when the shipper adds 4 additional stops (6-stop load), they pay on average \$96 per

additional stop, which is \$384 in SOC. The most common stop-off charges are \$50 and \$100 per additional stop. There are also cases where there is no Stop-off Charge.

SOC and First carrier acceptance

Shippers usually set a uniform SOC across carriers, but there are instances where they set different SOC's even with the same carrier. Figure 7 is a plot of shippers and their SOC per additional stop, where each bubble is a shipper and the size of the bubble is the number of stops. We observed that in general, as the number of stops increases (size of the bubble increases), the stop-off charge also goes up.

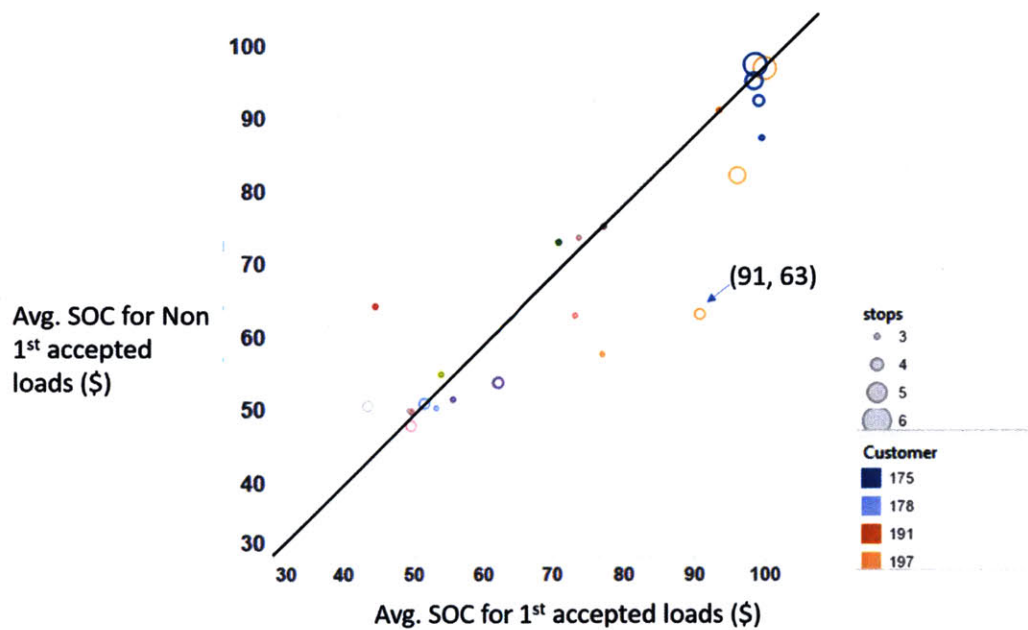


Figure 7. SOC per additional stop for different shippers. Bubble represents individual shippers, size of the bubble denotes number of stops

The X-axis represents the average stop-off charge paid for loads accepted by the first carrier and the Y-axis represents the average stop-off charge paid for loads not accepted by the first carrier for the same customer. Anything falling on the 45 degree line means that the shipper

pays a uniform SOC regardless of whether the tender is accepted by the first carrier or by others. However, most of the shippers fall below the 45 degree line – meaning that they pay more SOC for loads with a first tender acceptance and less for loads with higher routing guide depth. For example, for shipper 197 and their 4-stop loads (with 3 additional stops), the average SOC paid for loads with a first acceptance is $\$91 * 3 = \273 and the average SOC for loads with non-first acceptance is $\$63 * 3 = \189 . Therefore, the graph shows that higher SOC is associated with higher first tender acceptance.

Hypothesis 6 (a): Multi-stop loads with higher SOC will have higher acceptance.

Some common SOC per additional stop include \$0, \$50, \$75 and \$100. The categories of SOC are:

- SOC < \$50 (base)
- $\$50 \leq \text{SOC} < \75
- $\$75 \leq \text{SOC} < \100
- $\text{SOC} \geq \$100$

Rate per Mile

Another major pricing component is the line-haul, rate per mile excluding accessorial. The relationship between line-haul and routing guide depth is complicated. Theoretically, the higher the line-haul, the more likely it will be accepted: higher line-haul, lower routing guide depth. However, since shippers maintain a routing guide that ranks the carriers based on price and service level, they tend to rank carriers with lower line-haul higher up. Caldwell and Fisher

(2008) observed that shippers pay more as their routing guide depth increases – higher routing guide depth, higher line-haul.

We plotted the number of stops and the corresponding average line-haul per mile in Figure 8.

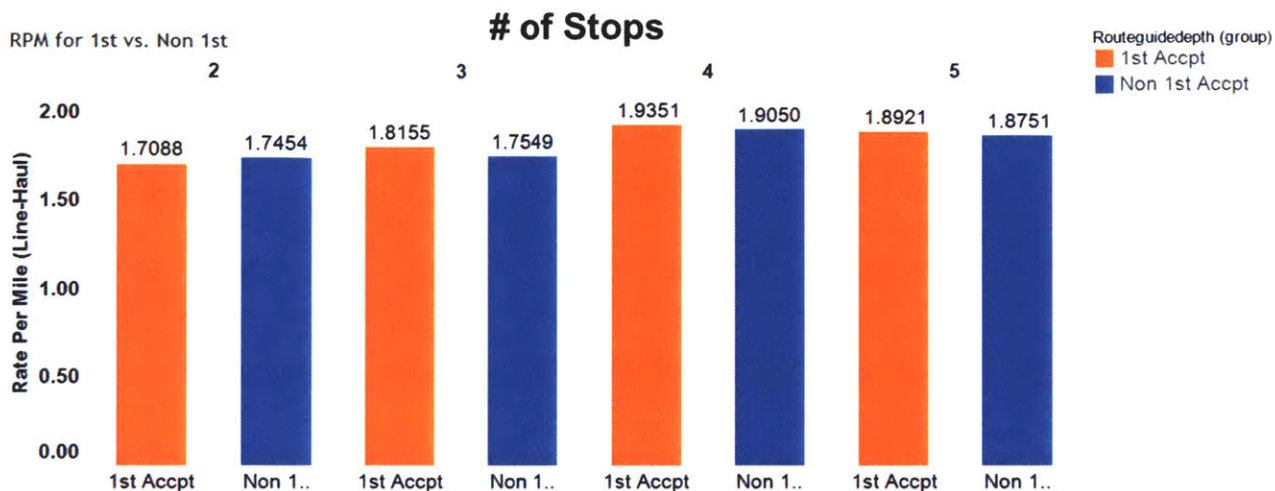


Figure 8. Line Haul Rate per Mile by Number of Stops

Tenders with routing guide depth greater than 4 were excluded, since the rates tend to get very expensive further down the routing guide. We broke it down by first acceptance and the non-first acceptance. The orange bar is the average line-haul for tenders accepted by the first carrier and the blue bar represents tenders not accepted by the first carrier. We found that as the number of stops increases, so will the line-haul per mile. For multi-stop loads, tenders accepted by the first carrier pay a higher line-haul than tenders not accepted by the first carrier.

However, the opposite is true for direct loads.

Due to the complex nature of their relationship, we will use it as an independent variable in order to identify their relation with all other factors controlled.

Hypothesis 7: Loads with higher rate per mile will have higher acceptance.

Lead Time

According to Caldwell and Fisher (2008), the longer the lead time, meaning the more advance notice is given to the carrier, the lower the price. According to their research, the impact of lead time is significant especially when lead time is low. In this case, loads are more likely to get rejected due to a lack of capacity by the carriers, and shippers often have to go to the spot market, which can be more expensive. Once the lead time reaches 6 days, the impact of lead time stabilizes.

Analysis of the distribution of lead times in our dataset yielded a mean lead time of 90 hours. We characterized the lead time into the following categories, which is slightly different from Caldwell and Fisher (2008)'s approach, to ensure we have enough records in each category for multi-stops.

- 0 - 16 hours (one to two working shift)
- 16 hours to 3 days
- Above 3 days (base case)

Origin and Destination States

To test for regional sensitivity, we created dummy variables for 48 origin states and 48 destination states, excluding Hawaii and Alaska. The origin state with the highest tender volume is Texas, which we chose as the base case for origin state. The destination state with the highest tender volume is also Texas, which we chose as the base case for destination state.

4.2 Results from Logistic Regression

All of the variables above were included into a logistic regression model and tested with our tender dataset. The results on Table 6 showed that most of the variables were significant at high significance values (99% level).

The McFadden's R^2 of 0.46 is considered high, meaning that the model does a good job of explaining the variation in acceptance.

Table 6. Tender Acceptance Logistic Regression Results. Complete table including origin/destination states is in the Appendix

Term	Estimate β	Std Error	ChiSq	Prob>ChiSq	Odds e^β
Intercept	4.24	0.29	210.53	<.0001	
volume_index	-0.05	0.00	417.51	<.0001	0.95
Outofroute	0.00	0.00	24.71	<.0001	1.00
continuousmove_indicator	1.08	0.06	315.64	<.0001	2.94
consecutivepickslessthan30	-0.08	0.07	1.19	0.27	0.92
consecutivedropslessthan30	0.28	0.02	134.24	<.0001	1.32
extradrop 1	-1.27	0.07	325.39	<.0001	0.28
extradrop 2	-1.41	0.08	329.75	<.0001	0.24
extradrop3plus	-1.16	0.09	172.14	<.0001	0.31
extrapick 1	-1.03	0.05	385.78	<.0001	0.36
extrapick 2	-1.06	0.13	67.05	<.0001	0.35
extrapick3plus	0.60	0.58	1.09	0.30	1.83
linehaul_rpm	1.74	0.04	2197.30	<.0001	5.71
miles	0.00	0.00	1321.20	<.0001	1.00
soc50_100	0.07	0.04	2.68	0.10	1.08
soc100_plus	1.71	0.07	681.66	<.0001	5.55
leadtime_ 0_16	2.19	0.07	985.53	<.0001	8.92
leadtime_16_72	0.55	0.02	503.85	<.0001	1.74
McFadden's R2					
0.4619					

Parameters obtained using logistic regression are not as straightforward to interpret compared with linear regression. One way of interpreting them is by using the logistic response function to derive probabilities. This method runs into the disadvantage that the changes in probability are relative and differ depending on the initial conditions: the effect of 100 extra miles on the acceptance probability will differ depending on whether it is from 100 to 200 miles or from 900 to 1000 miles. Another way of interpreting it is by calculating the odds, where

$$Odds = e^{\beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_k * x_k} = \frac{P}{1 - P}$$

In this case, by calculating $e^{\beta_1 * x_1}$ for each coefficient we can quantify the effect of each variable on the odds. If $e^{\beta_1 * x_1} > 1$, the effect is positive, if $e^{\beta_1 * x_1} < 1$, it is negative.

For example, for *extradrop1*, $e^{-1.27} = 0.28$. This means that having one extra drop will affect the odds of acceptance by a multiplicative factor of 0.28. If the odds were previously 1:1, having one extra drop will decrease them to 0.28:1, or from 50% to 21.875%.

We follow with an analysis of results in that format.

Out-of-Route Miles

The impact of out-of-route miles on acceptance is negative at a 99% confidence level, confirming our initial hypothesis. However, the magnitude of this effect is relatively small. With 500 out-of-route miles, the multiplicative factor is 0.80, meaning the odds are decreased by 20% (and 1:1 would turn into 0.8:1 or equivalently 50% to 44.6%). With 300 out-of-route miles, the odds decrease by 12.3%. With 100 out-of-route miles, the odds decrease by 4.3%. When

the out-of-route miles are extreme, it may sway the acceptance decision, but if the out-of-route miles are less than 100 the effect is negligible.

Clustering

Clustering increases the likelihood of acceptance. For picks, the effect is negligible and not significant. Clustering 3 or more drops together, however, affects the acceptance positively at a 99% confidence level. The increase in acceptance for clustered drops is equivalent to a 32% increase in odds, which assuming an initial acceptance probability of 50% before clustering would become 57% following clustering all else equal.

Continuous Move

Having a route with a continuous move significantly increase the odds of acceptance. The effect is larger than that of clustered drops, and is consistent with the fact that continuous moves reduce empty miles for carriers. Changing a multi-stop with an acceptance rate of 50% so that it becomes a continuous move would increase the acceptance rate to almost 75% all things equal.

Additional Stops

Additional picks and drops both decrease the likelihood of acceptance at the 99% significance level. The negative effect of extra drops on acceptance rate is larger than the effect of extra drops. For one extra drop, the odds decrease by 72% while for one extra pick they decrease by 64%. Given initial acceptance odds of 1:1 or 50%, this would translate to 0.28:1 odds or 22% after adding 1 extra drop and 0.35:1 or 26% after adding 1 extra pick.

The degree of the impact depends on the number of extra drops: having 2 extra drops decreases the acceptance odds further, by 76% instead of just 72% for 1 extra drop. Adding 3

or more drops decreases the odds overall as well, but not to the same extent that adding 1 or 2 drops does. One possible explanation is that multi-stop loads with 3 or more extra drops are known in advance to some extent (either planned or communicated beforehand).

For picks, the difference in acceptance odds between 1 extra pick and 2 extra picks is only 5%. Given the standard error, it is possible that the true value of the parameters overlap and are essentially the same. We can see that having 3 or more extra picks is not significant for determining order acceptance: this is most likely due to the lack of records with 3 or more extra picks.

Line Haul and Stop-Off Charges

Line-haul rate per mile increases improve the odds of acceptance: a \$0.10 increase in rate per mile increases the odds of acceptance by roughly 19%. The line-haul rate per mile is usually within a limited range, thus increases in odds should be analyzed within it.

Overall, paying stop-off charges also seems to increase the acceptance rate. However, effect of paying between 50 and 75 per extra stop is not significant at the 99% or 95% significance levels. The real increase in acceptance rate occurs when the stop-off charge is 100 or more, with 5.55 times the odds of acceptance. This increase is sizeable: assuming an acceptance rate of 50% without stop-off charges, the acceptance rate would jump to 85% after adding a \$100 per additional stop SOC.

Origin and Destination Lanes

As there are 96 variables for origin and destination state, we display their effects on the odds superimposed on a map in Figures 9 and 10 for ease of interpretation.

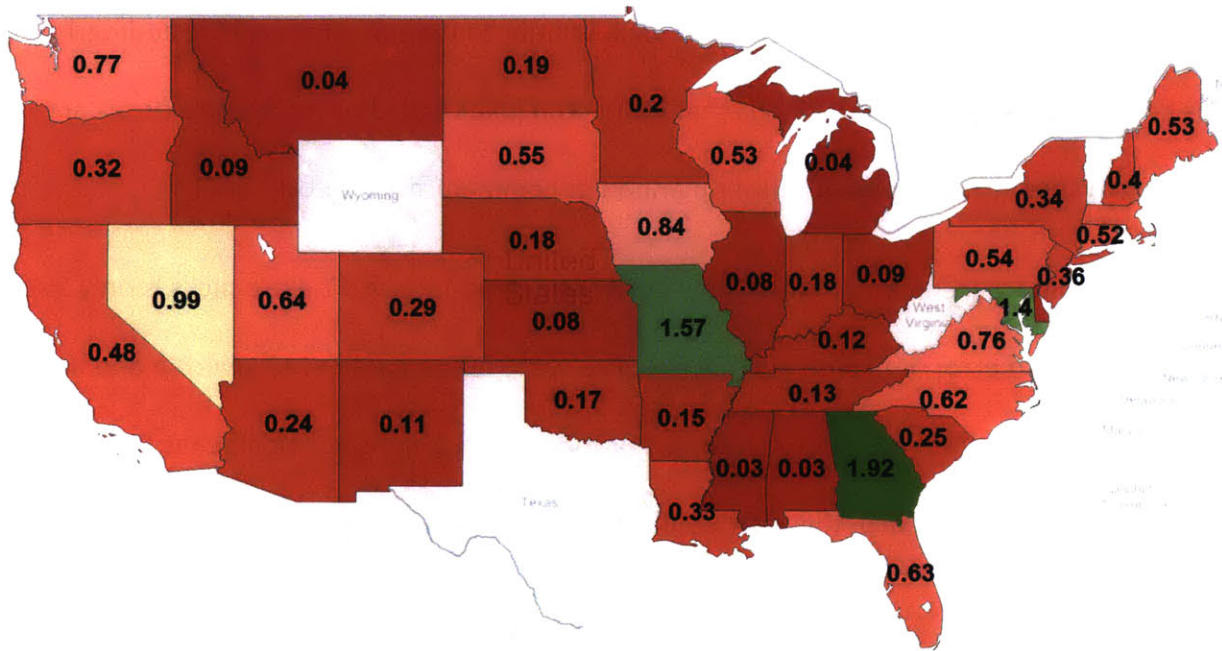


Figure 9. Multi-Stop Acceptance Odds by Origin State relative to Texas. States other than Texas which are greyed out have insufficient data points

Having a load originate from Montana, Mississippi, Alabama or Michigan can decrease the acceptance odds by over 96% relative to Texas. Notably, originating from Georgia and Missouri increases the odds of acceptance slightly, which may be due to dynamics involving routes in those particular states. Some states, including Wyoming and West Virginia, are excluded from the analysis owing to lack of data points. Relative to each other, the Western and Eastern coasts have higher odds of acceptance compared to states in the interior such as North Dakota and Nebraska.

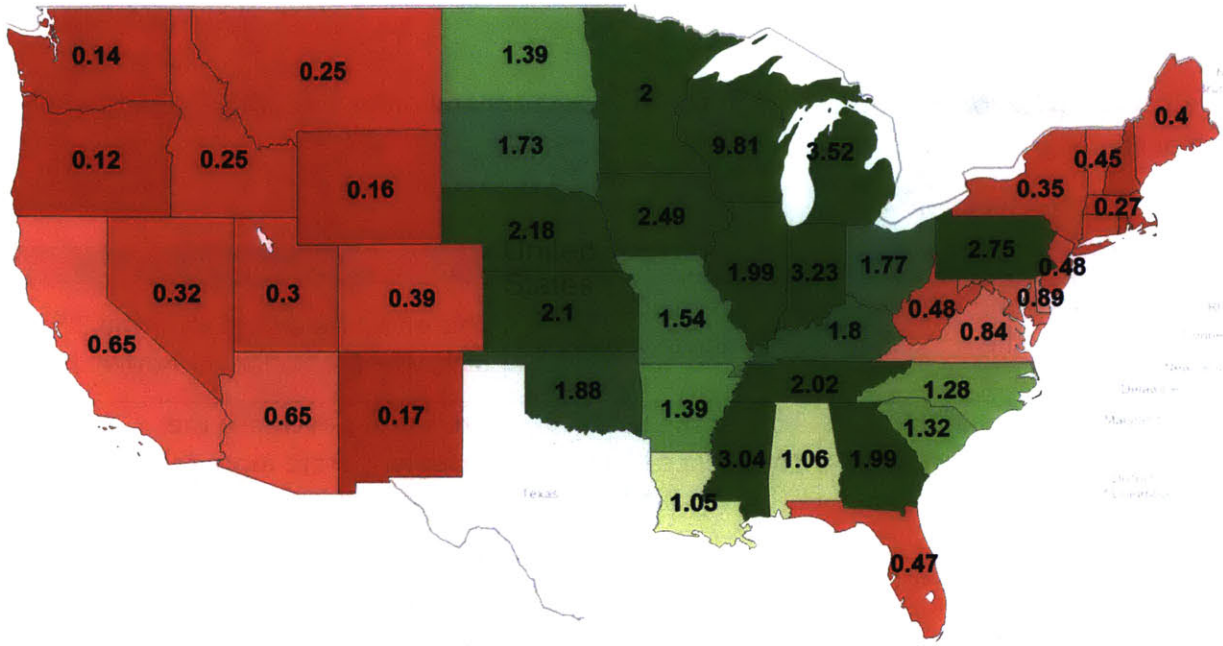


Figure 10. Multi-Stop Acceptance Odds by Destination State relative to Texas. States other than Texas which are greyed out have insufficient data points

Conversely, going to the West and the Northeast can decrease the acceptance rate relative to going to Texas. Some states in the interior features better acceptance odds when they serve as destinations; however, this effect is relatively tempered.

Modeling the regional effect separately for single stops and multiple stops showed that there is a significant difference in the impact of the origin/destination states on acceptance depending on whether it is single or multiple stop. For multiple stop, negative effects were markedly more pronounced in most states, showing an increased sensitivity. Georgia was remarkable insensitive and tolerant of multiple stops, showing no increase or decrease in acceptance rate.

4.3 Summary

Table 7 summarizes our hypotheses about carrier behavior and order acceptance together with the main findings.

Table 7. Carrier Behavior Hypothesis Results

Hypothesis	Result	Comments
H1(a): The more additional stops, the lower the acceptance.	True at the 99% confidence level.	This effect tapers off after the 3 rd pick, which is no longer noticeable.
H1(c): The impact of additional stops on acceptance will differ depending on whether it is a pick or a drop.	True at the 99% confidence level.	Extra drops decrease the acceptance rate more than extra picks do.
H2(a): The more out-of-route miles, the lower the acceptance.	True at the 99% confidence level.	For less than 100 out-of-route miles, the effect is quite negligible.
H3(a): The more demand as reflected in the market index, the lower the acceptance.	True at the 99% confidence level.	
H4(a): Continuous moves have a higher acceptance rate	True at the 99% confidence level.	The effect of a continuous move on the acceptance odds is more than twice that of clustered drops.
H5(a): Loads with clustered stops have a higher acceptance.	True at the 99% confidence level for clustered drops. Not so for clustered picks	Clustering picks is not significant at the 95% confidence level.
H5(c): The impact of clustered stops on price and acceptance will differ depending on whether it is a pick or a drop.	True at the 99% confidence level.	
H6(a): Multi-stop loads with higher SOC will have higher acceptance rates.	True at the 99% confidence level for SOC >=100.	For SOC between 50 and 75, the effect is not significant.
H7: Loads with higher rate per mile will have higher acceptance.	True at the 99% confidence level.	There is a 19% average increase in acceptance odds for every 10 cent increase in rate per mile.

5. MULTI-STOP TRUCKLOAD PRICING

In this chapter, we explore the factors that impact the actual rate per mile paid (line-haul excluding the accessorial costs). We present some data visualization showing the relationship followed by the results of the pricing model (linear regression model).

5.1 Data Analysis

Impact of Additional Stops

To obtain insight into how price responds to an increase in number of stops, we looked at the total rate per mile (total amount paid divided by miles) corresponding to each pick/drop combination. As shown on Table 8, the average rate per mile for direct loads is \$2.16. The price is highest for 1 pick 3 drop loads at \$2.48 on average. We can see a general trend of price going up as the number of drops increases. The trend is not very consistent with the picks. To better understand the effect of multi-stop on pricing, we need to control for many variables other than stops, such as lead time. Therefore, we will examine the relationship further by building a linear regression model to predict price in the next section.

Table 8. Rate per Mile depending on number of Picks and Drops

Rate/Mile		Drop		
		1	2	3
Pick	1	\$ 2.16	\$ 2.35	\$ 2.48
	2	\$ 2.02	\$ 2.43	\$ 2.34
	3	\$ 2.14	\$ 2.12	\$ 2.45

Hypothesis 1 (a): the more additional stops, the higher the price.

SOC and Line-haul

The previous section implied that shippers pay more for multi-stop loads, which may be partly due to the stop-off charges. Another question of interest is whether there is an implicit cost for multi-stops that is baked into the line-haul- that is: do multi-stops pay a higher line-haul? Does a higher SOC imply a lower line-haul? And is there a market rate regardless of whether it is paid in SOC or line-haul? Table 9 compares the line-haul per mile for SOC per additional stop of \$50 and SOC per additional stop of \$100. While the difference is imperceptible for 3-stop loads, the line-haul is lower for SOC of \$100 for 4-stop and 5-stop loads. Therefore, we make the following hypothesis:

Hypothesis 6 (b) Multi-stop loads with higher SOC have lower line-haul price.

Table 9. Line-Haul Rate per Mile depending on Stop-off Charge

Line-haul \$ SOC/ Additional Stop	# of Stops		
	3	4	5
\$50	\$ 1.98	\$ 2.01	\$ 2.02
\$100	\$ 1.98	\$ 1.99	\$ 1.91

Planned vs. Unplanned

Shippers usually negotiate transportation contracts with their carriers annually, and will agree on a line-haul per mile for each lane as well as accessorial including SOC. Sometimes shippers know beforehand that there will be multiple stops in a given lane, and might take this into consideration when negotiating the rates on that lane. In that case, we define the multi-stop load as **planned**. In other cases, carrier and shipper negotiate the line-haul treating it as a direct haul, possibly due to the fact that the shipper didn't originally plan on using multi-stop loads for that lane at the time of negotiation. We define these multi-stop loads as **unplanned**. Our hypothesis is that the carrier will charge a premium for unplanned multi-stop loads. In our

dataset, we don't have a record for whether a multi-stop load is planned. As a result, we use the following variable as a proxy: planned loads are the ones that occur at least every other week and have the same line-haul rate and SOC every time.

Hypothesis 8. Multi-stop loads that are planned have a lower price.

5.2 Pricing Model

To understand the impact of multiple stops on the price that shippers end up paying, we used linear regression to model prices. Ordinary Least Squares is a regression method that minimizes the difference between the actual price paid by the shipper and the price predicted by the model. Using this method, we identified factors or features that are significant in predicting the true price of a truckload.

$$Y = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_k * x_k + e$$

The linear regression equation is show above, where Y is the dependent variable price and x_1 through x_k are independent or explanatory variables. The error term e is assumed to be normally distributed.

To evaluate our pricing model we used adjusted R^2 as a measure of fit, together with p-values to evaluate the statistical significance of our chosen factors.

5.2.1 Pricing Definition

In the full truckload market, price is composed of line-haul and accessorial cost. Line-haul is the pre-determined contract price for each route, expressed in dollars per mile. It is mainly determined by the origin and destination location, and how well these routes fit into the

carrier's network. Accessorial fees refer to extra costs associated with services other than just driving. Common examples of these charges include fuel surcharges, detention charges, and in case of multi-stop loads, stop-off charges.

A fuel surcharge is charged according to the current price of fuel. Although shippers get an estimate of the surcharge at the time of tender, the price may change due to fuel price fluctuations. Detention charges are penalties charged to shippers when they fail to load or unload the trailer within a certain period of time (normally 2 hours). The rationale is that drivers are paid by hours on the road. If they are held up at the shipping facilities for too long, it is opportunity cost forgone.

Having multiple stops means that the driver has to drive more out-of-route miles for intermediate stops, and that the risk of delay also increases as more time is spent loading and unloading. Therefore, not only does the total line-haul cost increase with miles driven, but shippers also need to pay a fixed fee, stop-off charge, which can be a flat fee across all stops or follows a stepped fee schedule (e.g. \$50 for the first additional stop, \$75 for the second additional stop, excluding origin and destination).

In summary, the price is determined by the below formula.

$$\begin{aligned} \text{Total Price (actual)} &= \text{LineHaul} + \text{Accessorial Cost} \\ &= \text{Rate per mile} * \text{Miles} + \text{Fuel Surcharges} + \text{Stop-off Charge} + \text{Detention Charge} \end{aligned}$$

The actual price paid could be slightly different from the price offered at tender. In our model, since we want to know what shippers actually pay, the actual total price is used. However, the price of diesel has fallen more than 35% since 2014. In order to understand the true cost of a

load regardless of fuel price fluctuation, we need to exclude the fuel surcharge in our price calculation.

5.2.2 Understanding fuel surcharges

Although the gas price per gallon is almost the same across the country at any given time, shippers can be charged very different per-mile fuel surcharges. The fuel surcharge is calculated based on the difference between the fuel rate published by the Department of Energy (DOE), and the peg rate, which is negotiated between the carrier and the shipper. If the fuel rate is below the peg, no surcharge is applied. The surcharge formula is shown below.

$$\text{Fuel Surcharge} = (\text{DOE fuel rate} - \text{peg rate}) / \text{Escalator} * \text{Surcharge fee}$$

Carriers may set different "peg" rates with different shippers, which complicate costs. For example, if a carrier sets a peg rate of \$1.2 with shipper A and \$1.5 with shipper B, and assuming the DOE fuel rate is \$2.0 with an escalator of 6 cents and surcharge fee of 1 cent: Shipper A's surcharge is $\$0.8 * 0.06 / 0.01 = \4.8 while shipper B has to pay a surcharge of \$3. Although shipper B is paying a lower surcharge, it is likely that B will pay a higher line-haul to account for an extra \$0.3 per gallon of fuel costs.

Therefore, in our model, instead of excluding the fuel cost from the actual total price, we exclude the standardized fuel cost that is calculated using a peg rate of \$1.2 per gallon.

$$\text{Per Mile Fuel Surcharge} = (\text{DOE fuel rate} - \$1.2) / 6$$

5.2.3 Dependent variable

In our model, we want to know whether there is implicit cost associated with multi-stops, or in other words, whether the cost of having multiple stops is baked into the line-haul. Thus, our dependent variable is only the line-haul, which can be calculated using the below formula.

$$Y = \text{Total Price (actual)} - \text{standard fuel surcharges} - \text{Stopoff Charges}$$

5.3 Pricing Model result

We developed a linear regression model to predict the price paid for each load, excluding the accessorial cost. After performing a linear regression, we found that all of the factors we identified are significant in determining price. The variables combined provide an adjusted R square of 85.98%, which means that they explain almost 86% of the variability in the total price.

All of the independent variables are significant at the 99% level with p-values less than 0.0001.

Since the p-values are all extremely small, we use the negative logarithm of the p-value to base 10 (sometimes also called the logworth) to rank the importance of a variable. The bigger the logworth of the P-value, the more important is the variable.

Ranked by importance, the most significant factors are distance, market index, additional drop-offs, lead time and Stop-off Charges. The less important ones are additional picks, clustering of the stops, out-of-route miles, planned vs. unplanned and continuous moves. The importance of origin and destination states vary across the states.

The result is summarized in Table 10.

Table 10. Pricing Model Regression Results Summary (excluding origin/destination information)

Term	Criteria	\$ Impact	Prob> t	-Log P
Constant	\$ per load	-1229.78	<.0001	
Distance	\$ per mile	1.37	<.0001	449261.8
Origin	Origin State	Various		
Destination	Destination State	Various		
Additional Pick-ups	0	Base Case		
	1	172.02	<.0001	405.744
	2	173.73	<.0001	40.763
	> = 3	532.94	<.0001	57.515
Additional Drop-offs	0	Base Case		
	1	304.93	<.0001	1350.333
	2	334.62	<.0001	1192.057
	> = 3	352.89	<.0001	1119.201
Out-of-Route Miles	\$ per mile	0.21	<.0001	317.746
Market Index	\$ per volume per week	11.38	<.0001	11456.26
Continuous Move	Non Continuous Move	Base Case		
	Continuous Move	-269.36	<.0001	496.991
# of consecutive drops < 30 Miles	\$ per leg	-81.82	<.0001	447.333
# of consecutive picks < 30 Miles	\$ per leg	-113.47	<.0001	57.631
Stop-off Charge	< \$50	Base Case		
	\$50 <= SOC < \$75	-247.54	<.0001	992.459
	\$75 <= SOC < \$100	-285.02	<.0001	835.484
	> = \$100	-221.46	<.0001	668.285
Planned	Not Planned	Base Case		
	Planned	-31.44	<.0001	15.179
Lead Time	0 - 16 hours	68.02	<.0001	1261.622
	16 hours - 3 days	13.06	<.0001	124.528
	> 3 days	Base Case		
Adjusted R Square		0.86		

One trend is that the destination or drop-off locations contribute more to the line-haul price than origin or pick-up locations. The shipper pays \$1.37 per mile, and \$0.2 per mile for any out-of-route miles on top of that. The shipper pays a premium when they start adding intermediate stops but will have savings if the stops are clustered or if the load is a continuous or planned move. The shipper incurs an extra cost if the tender lead time is within 3 days. As predicted, paying a SOC reduces the line-haul rate.

Scenario Analysis

Based on the dollar impact of each variable, we compared the worst and best case scenarios as shown in Table 11 below. We chose a three-stop load with one additional drop, the most common type of multi-stop, to make the comparison. In both cases, shippers has to pay a penalty of \$304.9 for adding an extra drop. However, in the best case scenario, it is planned ahead of time and it is a continuous move with the additional drop being clustered. Assuming the shipper gives advance notice, and pays a SOC of \$75, the shipper ends up saving \$287.72 (The negative in the total cost means savings). On the other hand, in the worst case scenario, the shipper cannot take advantage of continuous move or clustering of the stops. If the shipper hasn't planned the load beforehand and tenders with a lead time of less than 16 hours, the shipper will have to pay a penalty of \$372.95. Although the shipper saves on SOC by not paying any, the result is a more expensive line-haul. Therefore, the worst multi-stop load will be \$660.7 more expensive compared to an optimized load, even if they have the same initial origin and final destination.

Table 11. Pricing Scenario Analysis

Criteria	Best scenario	Bonus	Worst scenario	Penalty
Additional Pickup	0	\$ -	0	\$ -
Additional Drop-off	1	\$304.93	1	\$304.93
Planned	Planned	(\$31.44)	Unplanned	\$ -
Continuous Move	Continuous	(\$269.36)	Non continuous	\$ -
Lead Time	> = 3 days	0	0 - 16 hours	\$68.02
# of consecutive drops	1	(\$81.82)	0	\$ -
SOC	\$75	(\$285.02)	0	\$ -
Total	Savings	(\$287.72)	Penalty	\$372.95

Additional Stops

Hypothesis 1 (b) and (c) cannot be rejected. The regression model shows that adding more stops does cost more and the cost implication is different for picks and drops. The cost of adding an intermediate pick and drop is around \$170 and \$300 per load respectively. The premium for picks is lower than for drops; one explanation is that when the shipper adds a pickup, it is usually located at a warehouse nearby. We also observed that as the number of stops increases, the cost premium goes up. In fact, the relationship between cost premium and additional drops is almost linear, with the equation

$$\text{Premium} = 23.98 * \text{additional drop} + 282.85$$

(R Square = 0.98). However, with additional picks, there is not much of a price difference between 1 or 2 additional picks- but a large premium is required when the third or fourth stop is added. Our model suggests that the line-haul price effect of any combination of picks and drops is additive: if there are 2 additional stops, one pick and one drop, the premium is \$172 + \$305 = \$477. Since our dependent variable is the line-haul (having stripped away fuel surcharges and accessorials such as stop-off charges), we therefore that shippers have to pay an additional rate per mile, on top of the stop-off charge, for multi-stop loads.

Distance and Out-of-route miles

Hypothesis 2 (b) cannot be rejected. The rate per mile is \$1.37, but there is a cost of \$0.2 per mile associated with out-of-route miles for multi-stop loads. Not only is the length of haul longer for multi-stops due to the nature of the stops, the shipper has to pay \$0.2/mile extra for

out-of-route miles on top of the per-mile rate. The more out-of-route miles, the more shippers need to pay to compensate for those miles.

Market Index

Hypothesis 3 (b) cannot be rejected. The Cass Truckload Index measures the market fluctuations of per-mile truckload pricing, excluding the accessorial costs: the higher the market index, the more expensive the load. This result shows that our data reflects the market fluctuations. Knowing the index for a particular month can help shippers better predict the price for that month.

Special Multi-stop Cases: Planned Loads and Continuous Moves

Hypothesis 4 (b) and Hypothesis 8 cannot be rejected. Our regression shows that whether the load is planned or a continuous move does make a difference at a high significance level.

All else being equal, if a load is a continuous move, our regression shows that the shipper saves \$269.36. If a load is planned, the shipper saves \$31.44.

The impact of continuous move is bigger than that of the planned move. This is because in a continuous move, the carrier is able to reduce empty miles and thus passes on the saving to the shippers. However, in a planned move, the only difference is consistency - the shipper tenders for the same route frequently. This may help carriers better plan their freight, though the savings are smaller.

Clustering of Stops

Hypothesis 5 (b) and (c) cannot be rejected. The regression model shows that if the stops are clustered, meaning there are at least two stops less than 30 miles apart, the load will be cheaper than if the stops are scattered. While previously we saw that the destination of a load and number of additional drops has a larger impact on pricing than the origin or additional picks respectively, the opposite holds true for clustering.

The clustering at pickups provides savings of \$113.47 per leg whereas the clustering at drop-offs provides savings of \$81.82 per leg. From the previous analysis, we know that if the shipper adds one additional pick, they will likely incur \$172.02 in additional cost. However, if the additional stop is less than 30 miles away from the origin, this additional cost can be offset due to the clustering effect and the shipper only pays \$58.55 more. Likewise, if the shipper adds one additional drop that is clustered, the additional cost is reduced to \$223, as opposed to \$305 not clustered. Therefore, shippers need to understand the implications of clustering their stops and strategically plan their routes to maximize savings.

To test the sensitivity of the clustering, we also ran the regression on consecutive drops/picks less than 60 miles apart, as seen in Table 12. The variables are also significant and though the exact magnitude of the impact differs, the overall dollar impact is the same as consecutive drops/picks less than 30 miles. In the previous example, one additional drop clustered within 30 miles of another drop cost \$223.11 (\$304.93 - \$81.82). If there is one additional drop clustered within 60 miles of another drop, the cost would be \$220.7 (\$319.61 - \$98.91). Therefore, a

stronger conclusion would be that as long as the stops are clustered within 60 miles apart from each other the clustering effect is fairly constant.

Table 12. Clustering Sensitivity Analysis

Term	X= 30 Miles		X= 60 Miles	
	\$ Impact	Prob> t	\$ Impact	Prob> t
Additional Pick-ups = 0	Base Case		Base Case	
Additional Pick-ups = 1	172.02	<.0001	213.53	<.0001
Additional Pick-ups = 2	173.73	<.0001	250.61	<.0001
Additional Pick-ups >= 3	532.94	<.0001	712.64	<.0001
Additional Drop-offs = 0	Base Case		Base Case	
Additional Drop-offs = 1	304.93	<.0001	319.61	<.0001
Additional Drop-offs = 2	334.62	<.0001	373.67	<.0001
Additional Drop-offs >= 3	352.89	<.0001	407.27	<.0001
# of consecutive drops < X Miles	-81.82	<.0001	-98.91	<.0001
# of consecutive picks < X Miles	-113.47	<.0001	-175.69	<.0001
Adjusted R Square	85.98%		86.02%	

Lead Time

When the lead time is within a day or two, the shipper has to pay a premium. Loads booked within 16 hours pay a premium of \$68.02 and loads booked within 1 to 3 days pay a premium of \$13.06 on average.

To understand the influence of lead time on direct and multi-stop loads, we ran a separate regression separating direct and multi-stops, but with the same variables. The result is shown in Table 13. Just like with direct loads, the lead time is still a significant factor for multi-stop loads; however, the dollar impact is smaller. Multi-stop loads booked with a short notice (less than a day) pay a premium of \$16.84, compared to a \$74.92 premium for direct loads. While a notice of 3 days is significant for direct loads, which have to pay a premium of \$13.63, it is not significant for multi-stops. Therefore, in multi-stop loads, the benefit of giving notice in advance is diminished, which is good news for shippers since multi-stop loads always take longer to

structure. As long as shippers give notice at least 16 hours in advance, they can avoid a premium of \$17.

Table 13. Lead Time Pricing Impact Summary

	Direct		Multi-stops	
Lead time	\$ impact	P-value	\$ impact	P-value
0 - 16 hours	74.92	<0.001	16.84	<0.001
16 hours to 3 days	13.63	<0.001	3.03	0.22
Greater than 3 days	Base case		Base case	
Adjusted R Square	85.22%		88.23%	

Regional Sensitivity

Origin and Destination region is known to be an important determinant of the attractiveness of a load as well as its price. For example, during produce season Florida becomes an attractive origin and destination.

To understand the impact of region on pricing, we ran regression solely for MSTL while keeping the same variables. Texas was used as the base case due to it being the state with the highest freight volume. Therefore, all the dollar impacts shown in the graph are relative to Texas. The adjusted R square is 88.7%, meaning the model explains 88.7% of the price variation for MSTL.

Origin states' pricing factors are shown on Figure 11. The lower the number (more negative), the cheaper it is to originate a multi-stop load from that state. The most expensive origin state is Vermont (with a premium of \$1470 compared to Texas) and the cheapest origin state is Massachusetts (with a discount of \$721 relative to Texas).

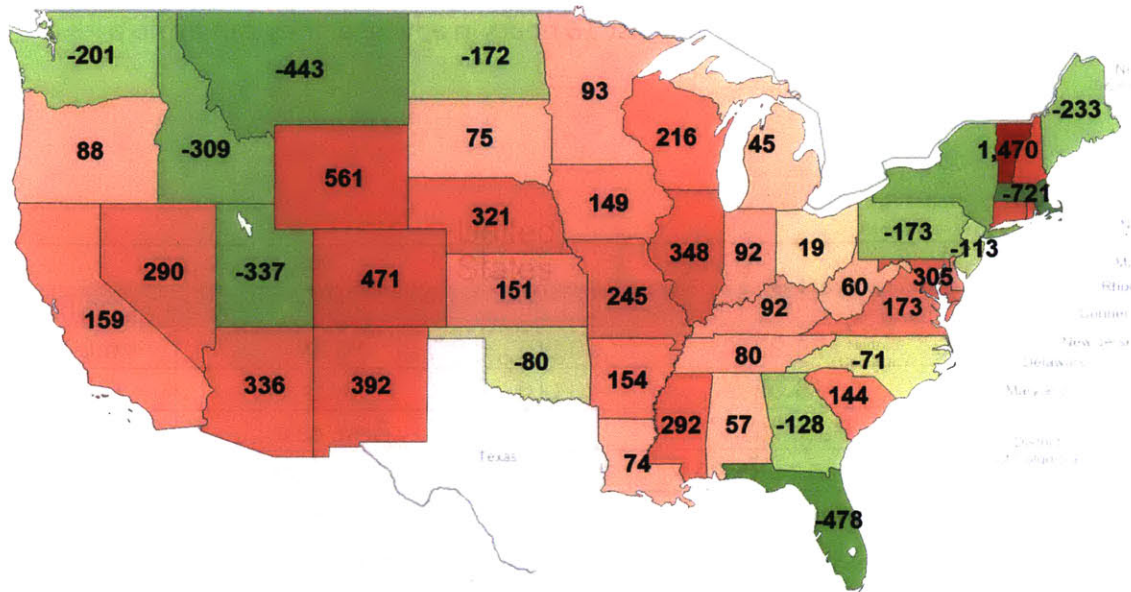


Figure 11. Price differentials for MSTL by origin state relative to Texas

Destination state factors are shown on Figure 12 below. Loads that go to the North East tend to pay the highest premiums and loads that go to California receive the highest discount.

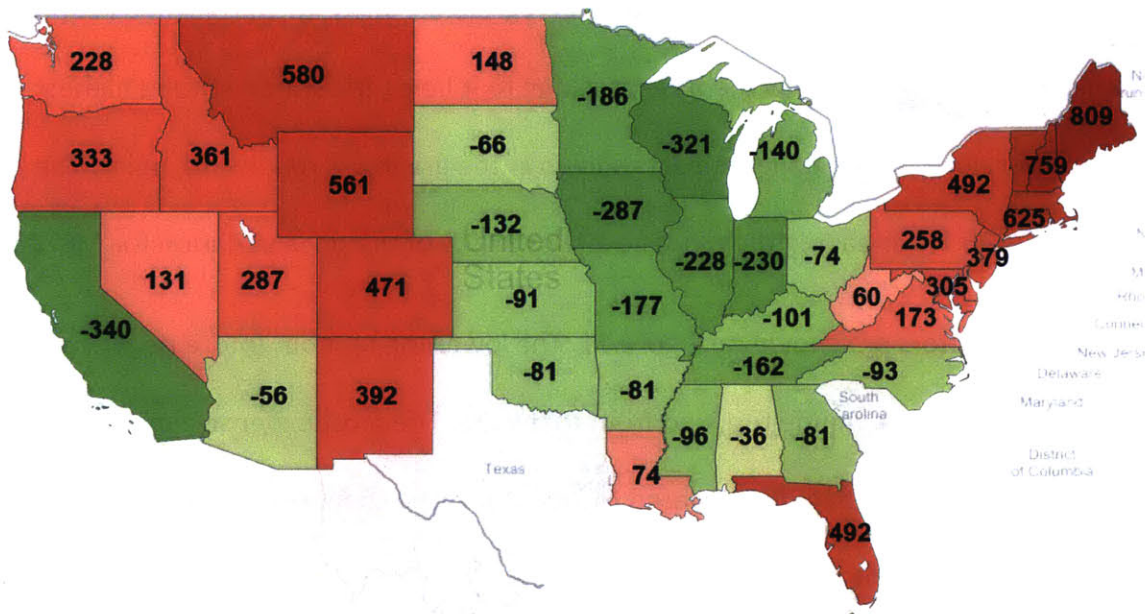


Figure 12. Price differentials for MSTL by destination state relative to Texas

We also see a reverse relationship between the attractiveness of the origin and destination as a state. The Northeast is not attractive as a destination, but is more attractive as an origin. In contrast, California is very cheap as a destination, and expensive as an origin. The regionality reflects the supply and demand imbalance of each state. To understand this imbalance, we also calculated the min to max ratio, defined as:

$$\text{Min to Max Ratio} = \text{Minimum rate from A to B} / \text{Maximum rate from B to A}$$

For example, from California to Florida, the premium is \$651 (\$159 + \$492) for a multi-stop load. Inversely, from Florida to California, the discount is \$818 (\$478 + \$340) for a multi-stop load. The Min to Max Ratio on this lane, for a \$4000 load is 0.68.

Stop-off Charges

Hypothesis 8 cannot be rejected – paying a stop-off charge will result in a lower rate per mile, but the relationship is not linear and there are significantly less savings when SOC increases beyond \$75. If the shipper pays a \$50 SOC per additional stop (the most common SOC between \$50 and \$75), they will save \$247.5 per load in line-haul compared to shippers who pay a SOC of less than \$50. If the shipper pays a \$75 SOC per additional stop (the most common SOC between \$75 and \$100), they will save \$37.5 more (for a total of \$285 savings). However, if the shipper pays \$100 SOC per additional stop (the most common SOC in the \$100+ range), they will only save \$221.5, less than what they could have saved with a lower SOC.

To better understand SOC norms and verify if there is a correlation between higher SOC for longer hauls and a lower SOC for shorter hauls, we ran the model on MSTL less than or equal to 1000 miles and loads greater than 1000 miles separately. The savings arising from \$50 SOC and

\$75 SOC are similar, therefore, we combined them into the category \$50 - \$100 SOC/additional stop. Table 14 shows that for under 1000 miles, having a SOC of \$100+ per additional stop saves \$133.84 while having a SOC of \$50 - \$100 per additional stop saves \$124.88. However, the extra saving of \$8.96 is minimal considering the shipper has to pay more SOC to realize the saving. For over 1000 miles, having a SOC of \$100+ saves \$81.6, which is far less than \$251.25, the savings that can be realized if the shipper pays \$50 - \$100 SOC. Therefore, we can conclude that the carriers charge a premium in line-haul if no SOC is paid and that setting a SOC of \$50 per extra stop provides the shipper with the greatest savings in rate per mile especially for longer hauls.

Table 14. Price Impact of Stop-Off Charges

	<= 1000 Miles		> 1000 Miles	
SOC	\$ impact	P-value	\$ impact	P-value
SOC > = \$100	(\$133.84)	<0.001	(\$81.60)	<0.001
\$50 <= SOC < \$100	(\$124.88)	<0.001	(\$251.25)	<0.001
SOC < \$50	Base case		Base case	
Adjusted R Square	83.69%		77.78%	

Price savings is not everything, however. From the order acceptance model, we learned that higher SOC leads to a higher probability of tender acceptance by the first carrier. In Figure 13 we plotted the routing guide depth for SOC of \$50 (in blue) and \$100 (in orange), for length of haul less than 1000 miles and greater than 1000 miles. The graph confirmed our belief that paying a higher SOC has the benefit of maintaining a low and relatively stable routing guide depth. The loads that pay \$50 have a routing guide depth of 3 if they are under 1000 miles and more than 4 if they are greater than 1000 miles. Therefore, if the shipper sets a SOC per

additional stop at \$50 to take advantage of cost savings in the line-haul, they need to be mindful that their tender acceptance will largely deteriorate, especially for longer hauls.

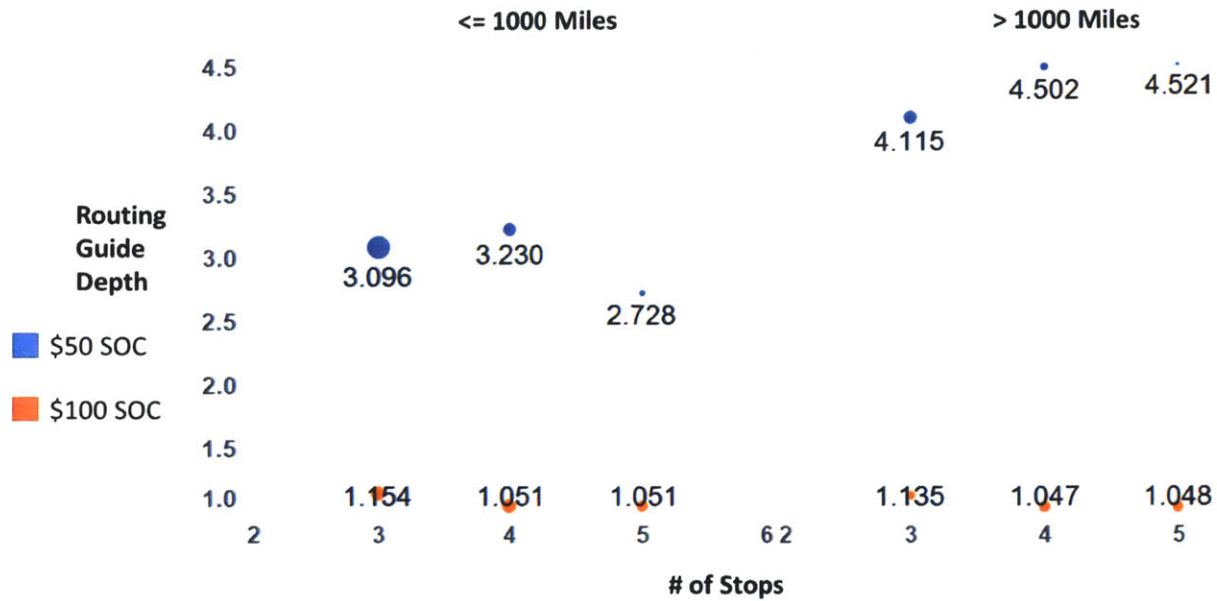


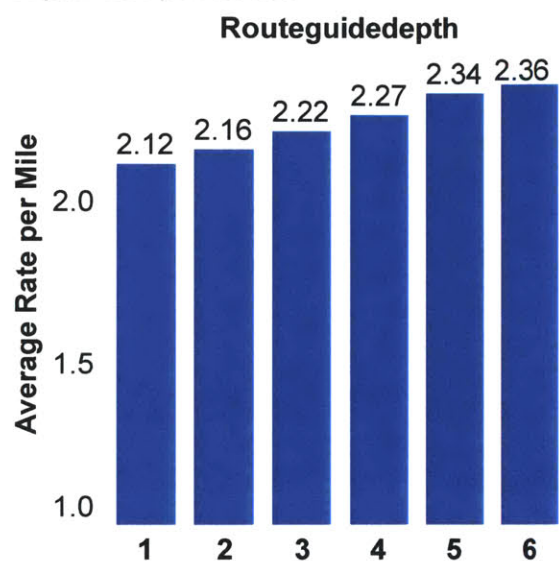
Figure 13. Routing Guide Depth by number of stops and stop-off charge

Normally, shippers have to pay extra as the tender goes deeper in the routing guide. It is counter intuitive that paying a \$50 SOC increases the routing guide depth, and reduces the cost at the same time. We suspect that the way shippers arrange their routing guide is different for MSTL. According to Caldwell and Fisher (2008), shippers typically place the cheapest carrier as their primary carrier and price is the dominant factor in determining a carrier’s position in the routing guide. We plotted the average rate per mile by routing guide depth for direct TL and MSTL in Figure 14 below.

For Direct TL, we observed the same relationship as Caldwell and Fisher (2008) – price increases as the routing guide depth increases. However, for MSTL, the primary and secondary carriers are not the cheapest. Since the loads that pay \$50 SOC have a routing guide depth of 3 on

average, their rate per mile ended up being the cheapest. This makes sense intuitively since for MSTL, shippers may put more expensive carriers as primary carrier to increase acceptance or on-time delivery performance.

depth vs. rpm direct



depth vs. rpm MSTL

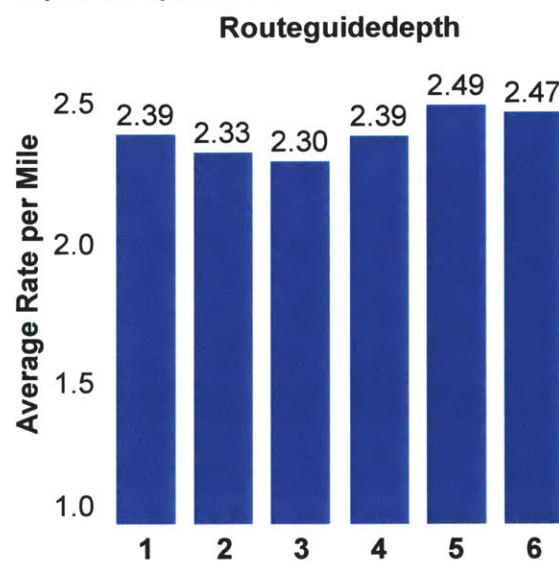


Figure 14. Rate per Mile according to Routing Guide Depth

To test it, we ran logistic regression on OTD (on-time delivery). OTD is a binary dependent variable, with 1 being on-time and 0 being not on-time. We used routing guide depth as independent variables - 1 is the base case, and the routing guide depth is coded as 2, 3 and 3+. The results on Table 15 show that routing guide depth is significant for both MSTL and Direct TL in determining On-time Delivery. However, the impact is larger for MSTL (with larger coefficient). The routing guide depth explains 0.5% of the variation in OTD for MSTL, but only 0.1% of the variation for Direct TL. Although the model lacks explanatory power, it still shows that shippers place more emphasis on service level when arranging their routing guide for MSTL.

Table 15. Logistic Regression results for OTD for Multi-Stop and Direct TL

Term	Criteria	MSTL		Direct TL	
		Coefficient	Prob> t	Coefficient	Prob> t
Constant		-1.75271	<.0001	-1.92376	<.0001
Routing Guide Depth	1	Base case		Base case	
	2	0.226945	<.0001	0.11545	<.0001
	3	0.464706	<.0001	0.205843	<.0001
	3+	0.484462	<.0001	0.257138	<.0001
R Square		0.005		0.001	

5.4 Pricing and Routing Guide Depth

The higher line-haul rate per mile seen for MSTL could be due to 2 reasons: it could be driven by rejections resulting in a higher routing guide depth (since the cheaper carriers tend to be placed first) or by a higher implicit cost imposed by carriers during negotiations (where savvy carriers anticipating MSTL loads might increase their line-haul during the bidding process).

We ran the same regression on the loads that are accepted by the first carrier in the routing guide to rule out the effect of routing guide depth increase. The results are displayed on Table 16 below.

Table 16. Impact of Extra Stops on Pricing

Term	All Data		1st Acceptance only	
	\$ impact	P-value	\$ impact	P-value
Intercept	-1229.78	<.0001	-905.36	<.0001
Additional Pick-up = 1	\$ 172.02	<.0001	\$ 132.59	<.0001
Additional Pick-up = 2	\$ 173.73	<.0001	\$ 160.94	<.0001
Additional Pick-up >= 3	\$ 532.94	<.0001	\$ 474.93	<.0001
Additional Drop-off = 1	\$ 304.93	<.0001	\$ 234.68	<.0001
Additional Drop-off = 2	\$ 334.62	<.0001	\$ 257.93	<.0001
Additional Drop-off >= 3	\$ 352.89	<.0001	\$ 271.24	<.0001
Adjusted R Square	85.98%		87.08%	

Even controlling for carrier acceptance by looking only at loads with routing guide depth of 1, there is still a price increase arising from additional picks and drops. This result lends credence to the hypothesis that savvy carriers implicitly bake the cost for multi-stop into the price.

Previous analysis showed that the biggest leap in both pricing and routing guide depth comes about when going from direct to adding one more stop. The price can increase by up to \$300 and the routing guide depth can jump by 0.5. Even if we control for the routing guide depth, the price for an extra drop still increases by \$233, which implies that the price increase comes from both a higher routing guide depth and a baked-in implicit cost. Figure 15 shows a loop diagram outlining this effect.

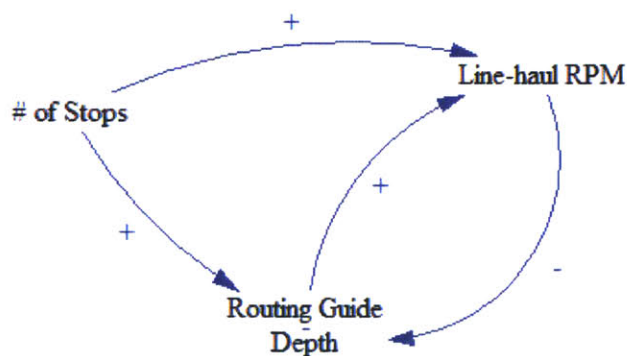


Figure 15. Causality diagram with arrows marking polarity of the effect

Line-haul RPM is affected directly by an increase in number of stops due to a routing guide depth increase, but also by carriers incorporating the cost implicitly into their yearly contracts. However, beyond the first additional stop, with 2 or more additional stops, we see a downward trend in routing guide depth while the price continues to climb. One interpretation is that carriers are able to better anticipate multi-stops with 2 or more additional stops and incorporate the pricing impact during the contracting period.

To conclude, the shipper is punished by having an additional stop on a haul, by incurring a higher implicit cost and getting more tender rejection. However, beyond the first additional stop, it is the rate per mile and the SOC that determines the acceptance/routing guide depth. As the shipper needs to pay more implicit cost for more stops, they get better tender acceptance in return.

5.5 Summary

To conclude, shippers moving from single stops to multiple stops will see a deterioration in tender acceptances and will pay higher rates per mile (essentially, the additional fees are baked into the line-haul rate per mile). However, beyond the initial additional stop, extra stops will improve the tender acceptance at the expense of an increased fee depending on whether the stop is a drop or a pick. One explanation as to why this might happen is the "diminishing sensitivity" principle explained by prospect theory in economics (Tversky and Kahneman, 1985), whereby participants who are willing to incur one unit of loss are also more likely to accept further losses.

Additional drops are generally more expensive at \$300 than additional picks at \$174. The costs don't increase linearly with extra stops: if more than 3 additional picks are added, the shipper seems to get punished by having to pay a substantially higher cost of more than \$500.

The payment structure also seems to matter. While two tenders might be identical in terms of stops, distance traveled, etc., the price charged will vary depending on whether that cost is displayed as a line-haul or a stop-off charge. This suggests the possibility of a "framing bias" by carriers. The shipper can thus achieve a savings of more than \$200 if they pay a Stop-off

Charge. Paying a stop-off charge of \$50 per additional stop saves more money than paying \$100 or not paying at all. However, although a lower stop-off charge is more cost efficient, it also tends to garner more tender rejections resulting in triple the routing guide depth.

The shipper has to pay an additional \$0.2 per out-of-route mile, but if the stops are clustered (2 stops are within 30 miles from each other), they can save up to \$100. Although Caldwell and Fisher (2008) suggested that shippers can save by money by giving a long lead time, our research shows that the saving is not as significant for multi-stop as it is for direct loads. However, shippers can save money and improve the tender acceptance if they plan their multi-stops at during annual negotiations with carriers. Shippers can further optimize this cost savings by structuring their routes as continuous moves, saving an additional \$270.

Table 17 summarizes the pricing hypotheses for multi-stop, together with the main findings.

Table 17. Summary of Hypotheses and Results

Hypothesis	Result	Result
H1(b): The more additional stops, the higher the price.	True at the 99% confidence level.	The price increases an average of \$170 for the 1 st additional pick and \$300 for the 1 st additional drop.
H1(c): The impact of additional stops on price will differ depending on whether it is a pick or a drop.	True at the 99% confidence level.	
H2(b): The more the out-of-route miles, the higher the price.	True at the 99% confidence level.	Shippers pay on average \$0.2 for every out-of-route mile, on top of the rate per mile.
H3(b): The more demand as reflected in the market index, the higher the price.	True at the 99% confidence level.	When there is more volume in a week, or more demand for the truckload, the price goes up.
H4(b): Continuous moves have a lower price.	True at the 99% confidence level.	Continuous moves are an average of \$270 cheaper compared to normal multi-stop.
H5(b): Loads with clustered stops have a lower price.	True at the 99% confidence level.	The shipper can save cost by clustering their stops.
H5(c): The impact of clustered stops on price will differ depending on whether it is a pick or a drop.	True at the 99% confidence level.	The average savings from clustering picks (\$113) is greater than that of clustered drops (\$81).
H6 (b). Multi-stop loads with higher SOC have lower line-haul price	True at the 99% confidence level.	Paying a stop-off charge will save shippers money on the line-haul. The greatest savings is achieved when shippers pay \$50 - \$75 per additional stop. The savings can often offset the stop-off charge.
H8. Multi-stop loads that are planned have a lower price	True at the 99% confidence level.	Planned loads have a lower price. If the shipper takes the additional stops into consideration in the negotiation process, they can save an average of \$31 per load.

6. CONCLUSION

6.1 Management Insights

Our research has implications for both shippers seeking to consolidate loads as well as carriers accepting these loads.

Many of the leading Transportation Management Systems (TMS) have features that enable consolidation of loads with one click. Consolidation can take the form of optimized routing, which may include multi-stops. If the transportation managers are not aware of the potential costs of multi-stop, and don't balance these against the benefits of consolidation, they may actually end up worse off by blindly following the TMS' recommendations.

For shippers who seek to save on transportation costs and are considering consolidating loads into multi-stops, our research suggests that it would be wise for them to consider the impact that MSTL really have. If they can understand that MSTL might lead to higher real prices, more delays in tender acceptance and more delays in shipment, they can make more informed decisions.

Shippers should bear in mind that having multiple stops incurs a latent cost (measured in our model as at least \$170/load for additional picks to \$300/load for additional drops). This cost is baked into the line-haul as an implicit cost and it is on top of the stop-off charge they normally pay. However, shippers can offset this cost by as much as \$200 if they pay a stop-off charge of \$50 per additional stop. The drawback of \$50 SOC is that they will get more tender rejections than if they pay a \$100 SOC, which is less cost efficient. In addition, while shippers mainly consider price in placing routing guide for direct TL, they place more emphasis on service level

when determining routing guide for MSTL. Therefore, as \$50 SOC tenders get more rejections, their on-time performance is also impacted. Shippers should also treat loads with clustered stops differently from the loads with scattered stops, as they have different implications on pricing. If the stops are clustered, the shipper can save up to \$100 per load, despite the increased cost for multi-stops. In addition, shippers can improve their tender acceptance if they plan their route with multi-stops considered. This principle of information sharing can help them save money when they negotiate the rate per mile with carriers.

For carriers, this research can help them understand their revealed preferences. By knowing how they are really behaving in reality (which can be hard in the absence of hard and fast rules), they can start to verify whether this behavior matches their real costs, and whether it makes sense. Carriers can also benchmark their current results against our findings to check if they are taking into account these costs into their strategies.

Knowledge about the impact of multi-stops on on-time delivery can also guide decision-making. Our research shows that shippers must be prepared for more delays, especially if the initial pickup is late, when dealing with multi-stops.

Optimizing the Routing Guide

Another way for shipper to use the insights is by determining which carriers have the best cost to tender acceptance ratios. This would have to be done for every lane and have to be updated periodically. The results of this analysis can be used to guide shippers' future procurement decisions, as well as for modifying the routing guide during the year. Figure 16 shows a plot of Acceptance Rate against Rate per Mile for an example lane, where each dot represents a

carrier. Carriers that are close to the upper left corner have a good ratio of cost to acceptance rate. One suggestion would be to place the ones with better ratios higher up on the routing guide, and to remove carriers that are dominated (have lower acceptance rates but higher costs), or to make those a target for renegotiation.

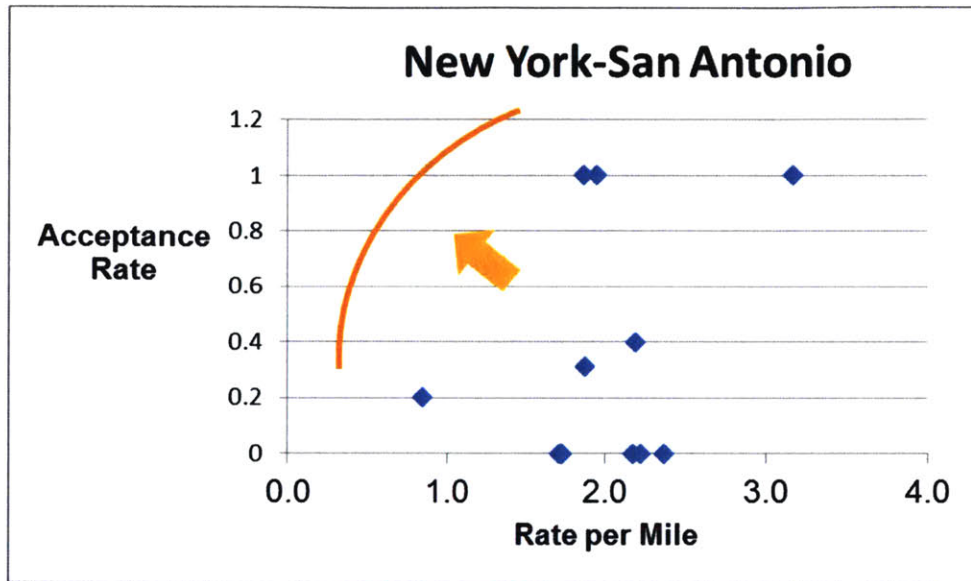


Figure 16. Acceptance rate vs rate per mile for New York-San Antonio lane

6.2 Future Research

Future research on multi-stop can build upon the analysis in this thesis to further quantify the impact on the bottom line.

More Complete Datasets

For future research, we advocate incorporating detention charges into the model if these are available. Although we made the conclusion about on-time delivery for multi-stop loads, it would have been better if we can know the monetary impact of delayed shipment, etc.

Future research might also look at how carriers can construct a pricing model that accurately accounts for costs through dynamic pricing. As of 2016 and with the evolution of logistics, carriers are starting to negotiate special rates for multi-stop. When this data starts being accessible, it will lead to a richer dataset that can be used for analysis. For instance, isolating the effects of multi-stop would be much more doable.

National, regional and local effects can also be quantified given enough information about the carriers. In our case, we had to manually match carrier name to fleet size and other characteristics. If this process can be automated so that for every tender we can know relevant characteristics of the carrier it is being offered to (fleet size, area in which it operates), the model can be refined to take those into account.

Other avenues of future research include building a more sophisticated prediction model for load acceptance using more advanced machine learning techniques such as bagging and boosting, especially given that trees seem to do a good job explaining the data.

Similarly, with the advent of more systematic collection of data including new hours of service regulation and tracking equipment such as Electronic On-Board Recorders (EOBR), we can look at the human factors that may affect multi-stop. Factors such as drivers' willingness to take hauls requiring multiple days to complete, and their personal predisposition to certain types of loads could be codified into the analysis. In addition, more accurate information regarding delivery windows and actual time spent at each stop would create a richer framework. Carriers' use of fleet management analytics software such as Omnitrac (formerly part of Qualcomm) could also portend changes in the behavior- changes that would be interesting to look into. On

this note, the rise of autonomous vehicles such as those pioneered by Volvo and Daimler might also spell significant changes to the future of truckload and MSTL for generations to come.

The introduction of multi-stop contracts with fixed pricing brings in interesting consequences. One way to anticipate them would be to collect data from Europe, where this type of contract is common.

System Bottlenecks and Little's Law

Another avenue of research would be to look at an individual shipper's tenders and see how much time they take on average to clear. This flow time could be measured to understand the real impact of rejections in dollar terms. Loads that go through the tendering process can be thought of as taking time W to be shipped. W includes the time it takes for a load to be accepted plus the lead time. Figure 17 shows the extra time needed to for a multi-stop shipment to be accepted.

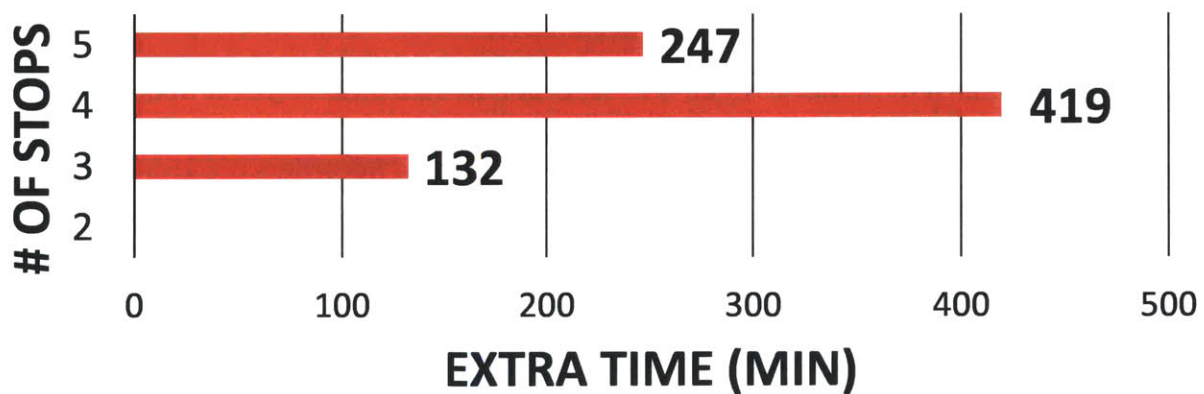


Figure 17. Extra time needed for multi-stop tender acceptance (2 stops is the baseline)

Thus, numerous rejections increase W .

$$L = \lambda W$$

Little's Law given above, where L is inventory, λ is flow rate and W is flow time, tells us that if we can decrease flow time W , the time it takes a load to exit the system, we can decrease the average inventory of loads waiting to be shipped and move towards higher efficiency. For supply chains where time is really important this can effectively be a bottleneck. In such a case, like in the automotive industry where Just-in-Time relies on shipments arriving at exact times and delays can hold back the entire operation, the "cost" of waiting for a tender to be accepted is no longer just the inventory holding cost, but a cost to the entire supply chain.

Strategy Comparison

Given enough information about shippers' routing guides, it would also be interesting to compare how different shippers' strategies might fare against each other. For example, a naïve strategy that ranks carriers in terms of ascending cost against a strategy designed to increase carrier acceptance without too much regard for cost, versus rules of thumb such as placing asset-based carriers first.

APPENDIX

I. Original Dataset Variables

Field	Example	Definition
LoadNum	162220640	TMC Shipment ID#
EnteredDate	11/20/2014 15:49	Date shipment entered TMC System
Ship Date	1/2/2015 0:00	Scheduled Ship Date
Mode	TL	Mode of transport
Temp Controlled	Dry	Temperature Requirement
Carrier	Ryan Transportation	Carrier Name
SCAC	RYNK	Carrier Code
Miles	2,018	Distance (miles)
MilesToNext		Miles to next stop on shipment
BranchCode	594	Customer Code Identifier
StopType	P	Stop Type: P=Pickup D=Delivery
StopNum	0	Stop number (0 is the first pickup)
WarehouseCode	W7045177	Unique Warehouse ID Code
Name	Pryor Stretch Film Way	Location Name
Address1	1 Stretch Film Way	Location Address
Address2		Location Address
City	Pryor	Location Address
State	OK	Location Address
Zip	74361	Location Address
Latitude	361549	Location Latitude
Longitude	951737	Location Longitude
OnTime	1	On Time: 0= late, 1=on time
RequestedDate	1/2/2015	Requested Date for pickup or delivery
SchedOpen		Scheduled Appointment Start Date/Time
SchedClose		Scheduled Appointment Close Date/Time
SchedReq	O	Type of Schedule Required (A: Appointment, N: Notify, O: Open Scheduling typically first come first serve)
ArrivalDT	1/2/2015 8:00	Actual carrier arrival date and time from the stop
DepartureDT	1/2/2015 10:00	Actual carrier departure date and time from the stop
Stop Dwell Time	2	Cycle time for loading/unloading (DepartureDT - ArrivatDT)
MaxWeight	27,158.00	Planned maximum weight of shipment

MinWeight	27,158.00	Planned minimum weight of shipment
ActualWeight	27,158.00	Actual weight of shipment
ExpPieces	21,410	Expected piece count of goods on shipment
ActualPieces	21,410	Actual piece count of goods on shipment
Exp Pallets	24	Expected pallets on shipment
ActualPallets	24	Actual pallets on shipment
LineHaul (Load)	\$3,006.82	Line-haul rate (Contracted/agreed rate)
Fuel (Load)	\$847.56	Fuel surcharge
StopOff (Load)	\$75	Aggregated stop off charge for the shipment
Detention (Load)	\$0.00	Detention at location for the shipment
Stop Off (Stop)	\$0.00	Stop off charge if allocated to the unique stop
Detention (Stop)	\$0.00	Stop off charge if allocated to the unique stop
SpotBid	NO	Indicates whether load was spot bid to get capacity
StopQuantity	1P2D	Stop Type: P = Pickup; D = Delivery; 1P1D = 1 Pick and 1 Drop
TotalStopCount	3	Total of all stops on shipment
Lane	Pryor,OK - Tumwater,WA	First pickup to last destination
% of Total Stops	33.30%	% that row is of the total stops (ex. 33.3% = 3 stop load)

II. Statistical Package Output

Output from the statistical packages for the different models is included below.

A1. Order Acceptance Model- Logistic Regression Output

Term	Estimate	Std Error	ChiSq	Prob>ChiSq	Odds
Intercept	4.24	0.29	210.53	<.0001	
volume_index	-0.05	0.00	417.51	<.0001	0.95
Outofroute	0.00	0.00	24.71	<.0001	1.00
continuousmove_indicator	1.08	0.06	315.64	<.0001	2.94
consecutivepickslessthan30	-0.08	0.07	1.19	0.27	0.92
consecutivedropslessthan30	0.28	0.02	134.24	<.0001	1.32
extradrop 1	-1.27	0.07	325.39	<.0001	0.28
extradrop 2	-1.41	0.08	329.75	<.0001	0.24
extradrop3plus	-1.16	0.09	172.14	<.0001	0.31
extrapick 1	-1.03	0.05	385.78	<.0001	0.36
extrapick 2	-1.06	0.13	67.05	<.0001	0.35
extrapick3plus	0.60	0.58	1.09	0.30	1.83
linehaul_rpm	1.74	0.04	2197.30	<.0001	5.71
miles	0.00	0.00	1321.20	<.0001	1.00
AL	-3.59	0.12	825.87	<.0001	0.03
AR	-1.92	0.16	137.48	<.0001	0.15
AZ	-1.41	0.10	199.29	<.0001	0.24
CA	-0.73	0.12	34.89	<.0001	0.48
CO	-1.25	0.47	6.95	0.01	0.29
CT	-0.66	0.75	0.78	0.38	0.52
DE	-2.26	0.12	330.09	<.0001	0.10
FL	-0.46	0.13	13.39	0.00	0.63
GA	0.65	0.10	44.56	<.0001	1.92
IA	-0.17	0.13	1.74	0.19	0.84
ID	-2.47	0.09	746.07	<.0001	0.09
IL	-2.48	0.08	1023.10	<.0001	0.08
IN	-1.74	0.07	594.48	<.0001	0.18
KS	-2.51	0.16	241.57	<.0001	0.08
KY	-2.15	0.10	430.78	<.0001	0.12
LA	-1.11	0.17	44.42	<.0001	0.33
MA	-0.65	0.60	1.17	0.28	0.52
MD	0.34	0.80	0.18	0.67	1.40
ME	-0.63	0.39	2.65	0.10	0.53
MI	-3.15	0.06	2600.20	<.0001	0.04
MN	-1.63	0.10	288.59	<.0001	0.20
MO	0.45	0.18	6.00	0.01	1.57
MS	-3.55	0.08	1780.20	<.0001	0.03
MT	-3.16	0.55	32.42	<.0001	0.04
NC	-0.47	0.13	13.49	0.00	0.62

ND	-1.69	0.24	47.55	<.0001	0.19
NE	-1.69	0.66	6.52	0.01	0.18
NH	-0.91	0.64	2.02	0.16	0.40
NJ	-1.01	0.20	26.90	<.0001	0.36
NM	-2.21	0.56	15.52	<.0001	0.11
NV	-0.01	0.13	0.00	0.96	0.99
NY	-1.07	0.15	54.54	<.0001	0.34
OH	-2.46	0.06	1693.20	<.0001	0.09
OK	-1.76	0.11	271.37	<.0001	0.17
OR	-1.14	0.22	27.74	<.0001	0.32
PA	-0.61	0.08	56.13	<.0001	0.54
SC	-1.38	0.10	201.34	<.0001	0.25
SD	-0.60	0.09	43.81	<.0001	0.55
TN	-2.01	0.08	635.06	<.0001	0.13
UT	-0.45	0.71	0.40	0.53	0.64
VA	-0.27	0.34	0.64	0.42	0.76
WA	-0.26	0.11	5.82	0.02	0.77
WI	-0.63	0.07	73.30	<.0001	0.53
D_AL	0.06	0.12	0.25	0.62	1.06
D_AR	0.33	0.15	4.68	0.03	1.39
D_AZ	-0.43	0.10	19.58	<.0001	0.65
D_CA	-0.44	0.06	54.97	<.0001	0.65
D_CO	-0.94	0.10	81.26	<.0001	0.39
D_CT	-1.16	0.15	60.10	<.0001	0.31
D_DE	-0.12	0.13	0.78	0.38	0.89
D_FL	-0.75	0.07	125.38	<.0001	0.47
D_GA	0.69	0.08	80.11	<.0001	1.99
D_IA	0.91	0.06	207.32	<.0001	2.49
D_ID	-1.37	0.16	72.75	<.0001	0.25
D_IL	0.69	0.07	110.81	<.0001	1.99
D_IN	1.17	0.11	106.49	<.0001	3.23
D_KS	0.74	0.14	30.06	<.0001	2.10
D_KY	0.59	0.13	19.64	<.0001	1.80
D_LA	0.05	0.11	0.20	0.65	1.05
D_MA	-1.31	0.10	155.24	<.0001	0.27
D_MD	-0.37	0.09	15.74	<.0001	0.69
D_ME	-0.91	0.15	38.16	<.0001	0.40
D_MI	1.26	0.08	265.53	<.0001	3.52
D_MN	0.69	0.06	117.40	<.0001	2.00
D_MO	0.43	0.09	22.01	<.0001	1.54
D_MS	1.11	0.14	62.79	<.0001	3.04
D_MT	-1.38	0.18	59.67	<.0001	0.25
D_NC	0.24	0.09	6.73	0.01	1.28
D_ND	0.33	0.11	9.36	0.00	1.39

D_NE	0.78	0.16	24.86	<.0001	2.18
D_NH	-1.47	0.20	55.38	<.0001	0.23
D_NJ	-0.73	0.08	76.55	<.0001	0.48
D_NM	-1.80	0.18	96.81	<.0001	0.17
D_NV	-1.14	0.21	29.77	<.0001	0.32
D_NY	-1.06	0.08	174.01	<.0001	0.35
D_OH	0.57	0.07	77.15	<.0001	1.77
D_OK	0.63	0.13	22.57	<.0001	1.88
D_OR	-2.12	0.13	257.18	<.0001	0.12
D_PA	1.01	0.06	258.65	<.0001	2.75
D_RI	-2.25	0.27	69.92	<.0001	0.11
D_SC	0.28	0.09	10.37	0.00	1.32
D_SD	0.55	0.17	10.58	0.00	1.73
D_TN	0.70	0.10	44.71	<.0001	2.02
D_UT	-1.20	0.14	75.07	<.0001	0.30
D_VA	-0.17	0.10	2.86	0.09	0.84
D_VT	-0.80	0.20	16.92	<.0001	0.45
D_WA	-1.94	0.11	317.08	<.0001	0.14
D_WI	2.28	0.07	951.26	<.0001	9.81
D_WV	-0.73	0.19	14.64	0.00	0.48
D_WY	-1.85	0.40	20.93	<.0001	0.16
soc50_100	0.07	0.04	2.68	0.10	1.08
soc100_plus	1.71	0.07	681.66	<.0001	5.55
leadtime_0_16	2.19	0.07	985.53	<.0001	8.92
leadtime_16_72	0.55	0.02	503.85	<.0001	1.74

A2. Pricing model – linear regression base model

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	-1229.78	6.01	-204.7	<.0001
miles	1.37	0.00	2180.4	<.0001
Add_picks 1	172.02	3.99	43.15	<.0001
Add_picks 2	173.73	12.88	13.49	<.0001
Add_picks>= 3	532.94	33.12	16.09	<.0001
Add_drops 1	304.93	3.87	78.89	<.0001
Add_drops 2	334.62	4.52	74.1	<.0001
Add_drops>= 3	352.89	4.92	71.8	<.0001
continuousmove_indicator	-269.36	5.64	-47.77	<.0001
consecutivedrops30	-81.82	1.81	-45.32	<.0001
consecutivepicks30	-113.47	7.05	-16.11	<.0001
leadtimeh0_16	68.02	0.89	76.24	<.0001
leadtime16_72	13.06	0.55	23.81	<.0001
planned	-31.44	3.89	-8.08	<.0001
out-of-route	0.21	0.01	38.16	<.0001
soc_>=100	-221.46	4.00	-55.43	<.0001
soc_50_75	-247.54	3.66	-67.59	<.0001
soc_75_100	-285.02	4.60	-62	<.0001
index	11.38	0.05	231.86	<.0001
MT	-19.67	16.04	-1.23	0.2202
RI	-332.64	44.53	-7.47	<.0001
VT	110.25	5.11	21.58	<.0001
WV	345.44	17.70	19.51	<.0001
AL	198.41	1.65	119.97	<.0001
AR	258.18	2.08	124.18	<.0001
AZ	127.43	2.04	62.35	<.0001
CA	339.42	1.56	217.61	<.0001
CO	-127.43	5.14	-24.78	<.0001
CT	-205.36	12.67	-16.21	<.0001
DE	-121.91	2.80	-43.6	<.0001
FL	-342.01	2.21	-154.8	<.0001
GA	47.70	1.51	31.49	<.0001
IA	227.97	1.62	140.67	<.0001
ID	26.78	4.60	5.83	<.0001
IL	270.37	1.43	189.03	<.0001
IN	239.04	1.46	163.97	<.0001
KS	250.93	2.67	93.91	<.0001
KY	214.66	1.76	121.79	<.0001
LA	79.88	3.53	22.62	<.0001
MA	-361.27	4.41	-81.95	<.0001
MD	-34.93	3.39	-10.3	<.0001
ME	79.46	23.96	3.32	0.0009
MI	212.99	1.63	130.67	<.0001
MN	332.51	1.54	215.55	<.0001

MO	239.04	1.86	128.36	<.0001
MS	380.22	2.77	137.24	<.0001
NC	143.19	1.27	112.67	<.0001
ND	81.59	5.69	14.33	<.0001
NE	285.43	7.62	37.46	<.0001
NH	-418.81	6.43	-65.11	<.0001
NJ	-231.49	2.31	-100.3	<.0001
NM	116.91	22.04	5.3	<.0001
NV	278.66	2.05	135.69	<.0001
NY	-82.33	2.48	-33.16	<.0001
OH	150.64	1.26	119.51	<.0001
OK	92.24	2.68	34.39	<.0001
OR	149.83	3.52	42.61	<.0001
PA	-75.00	1.52	-49.22	<.0001
SC	170.11	1.88	90.39	<.0001
SD	280.68	3.59	78.12	<.0001
TN	288.02	1.41	203.91	<.0001
WY	394.95	47.30	8.35	<.0001
UT	-111.27	12.10	-9.19	<.0001
VA	85.60	3.56	24.08	<.0001
WA	-18.51	2.08	-8.88	<.0001
WI	361.91	1.36	265.34	<.0001
D_AL	-86.97	1.82	-47.69	<.0001
D_AR	-74.86	3.78	-19.83	<.0001
D_AZ	-146.50	1.80	-81.25	<.0001
D_CA	-389.33	1.36	-286.3	<.0001
D_CO	347.80	2.28	152.54	<.0001
D_CT	530.33	4.55	116.44	<.0001
D_DE	248.83	2.75	90.62	<.0001
D_FL	347.85	1.49	233.34	<.0001
D_GA	-64.28	1.50	-42.93	<.0001
D_IA	-226.14	1.34	-169	<.0001
D_ID	158.06	4.66	33.9	<.0001
D_IL	-225.10	1.32	-170.1	<.0001
D_IN	-181.20	1.70	-106.3	<.0001
D_KS	-92.31	2.38	-38.8	<.0001
D_KY	-91.77	2.10	-43.63	<.0001
D_LA	38.69	2.98	12.97	<.0001
D_MA	575.93	2.65	217.04	<.0001
D_MD	293.04	3.07	95.48	<.0001
D_ME	574.50	4.40	130.49	<.0001
D_MI	-103.76	1.89	-55.04	<.0001
D_MN	-170.14	1.69	-100.5	<.0001
D_MO	-149.87	1.58	-94.73	<.0001
D_MS	-176.36	3.05	-57.79	<.0001
D_MT	586.65	6.70	87.57	<.0001

D_NC	-39.41	1.56	-25.34	<.0001
D_ND	0.27	3.72	0.07	0.9426
D_NE	-71.83	4.08	-17.6	<.0001
D_NH	608.93	5.79	105.24	<.0001
D_NJ	421.16	2.25	186.87	<.0001
D_NM	290.48	4.75	61.18	<.0001
D_NV	-84.24	2.52	-33.45	<.0001
D_NY	409.10	2.01	203.25	<.0001
D_OH	-82.28	1.33	-61.95	<.0001
D_OK	5.34	3.13	1.71	0.0877
D_OR	275.04	2.65	103.65	<.0001
D_PA	260.96	1.42	184.28	<.0001
D_RI	610.68	12.11	50.41	<.0001
D_SC	-87.64	1.92	-45.54	<.0001
D_SD	-16.90	5.46	-3.09	0.002
D_TN	-166.75	1.53	-109.2	<.0001
D_WY	397.06	6.70	59.24	<.0001
D_UT	149.79	2.99	50.13	<.0001
D_VA	181.82	2.24	81.06	<.0001
D_VT	525.68	5.67	92.75	<.0001
D_WA	262.14	2.17	120.8	<.0001
D_WI	-253.89	1.63	-155.3	<.0001
D_WV	121.45	7.53	16.12	<.0001

A3. Pricing model – Consecutive stops < 60 miles

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	-1224.962	6.000053	-204.2	<.0001
miles	1.371654	0.000629	2180.2	<.0001
Add_picks 1	215.21324	4.3136	49.89	<.0001
Add_picks 2	250.42969	13.23599	18.92	<.0001
Add_picks>= 3	714.30061	33.33265	21.43	<.0001
Add_drops 1	318.5165	3.932487	81	<.0001
Add_drops 2	374.29447	4.6434	80.61	<.0001
Add_drops>= 3	407.98494	5.081867	80.28	<.0001
continuousmove_indicator	-298.2244	5.685418	-52.45	<.0001
leadtimeh0_16	68.265542	0.890881	76.63	<.0001
leadtime16_72	13.208615	0.547985	24.1	<.0001
out-of-route	0.1396043	0.005475	25.5	<.0001
planned	-3.528358	3.854227	-0.92	0.36
soc_>=100	-210.4359	4.040621	-52.08	<.0001
soc_50_100	-236.0476	3.657046	-64.55	<.0001
index	11.347868	0.049043	231.39	<.0001
consecutivePlessthan60	-174.6071	6.339798	-27.54	<.0001
consecutiveDlessthan60	-98.98571	1.38997	-71.21	<.0001

A4. Pricing model – Direct & MSTL run separately

Term	MSTL				Direct			
	Estimate	Std Error	t Ratio	Prob> t	Estimate	Std Error	t Ratio	Prob> t
Intercept	-1212.33	26.13	-46.4	<.0001	-1209.12	6.14	-197.00	<.0001
miles	1.49	0.00	515.14	<.0001	1.37	0.00	2154.60	<.0001
leadtimeh0_16	16.84	3.27	5.16	<.0001	74.92	0.93	80.61	<.0001
leadtime16_72	3.04	2.48	1.22	0.2215	13.63	0.56	24.41	<.0001

A5. Pricing model – Regional sensitivity, MSTL only

Type	state	coefficient	Std Error	t Ratio	p-value
origin	MT	-442.8505	86.72354	-5.11	<.0001
origin	VT	1470.0032	334.2431	4.4	<.0001
origin	AL	57.29392	14.3163	4	<.0001
origin	AR	154.06347	19.29512	7.98	<.0001
origin	AZ	335.66623	10.82927	31	<.0001
origin	CA	159.3486	13.56802	11.74	<.0001
origin	DE	132.03751	14.56246	9.07	<.0001
origin	FL	-478.0128	15.63502	-30.57	<.0001
origin	GA	-127.686	6.147435	-20.77	<.0001
origin	IA	148.86385	8.810145	16.9	<.0001
origin	ID	-309.1094	10.10605	-30.59	<.0001

origin	IL	348.3459	8.098322	43.01	<.0001
origin	IN	92.02345	7.885049	11.67	<.0001
origin	KS	151.00108	21.80305	6.93	<.0001
origin	KY	92.31995	13.12184	7.04	<.0001
origin	MA	-721.3145	55.99309	-12.88	<.0001
origin	ME	-233.2579	55.11909	-4.23	<.0001
origin	MI	45.485572	6.285302	7.24	<.0001
origin	MN	93.072277	11.57647	8.04	<.0001
origin	MO	245.36348	11.03847	22.23	<.0001
origin	MS	291.69501	9.431439	30.93	<.0001
origin	NC	-71.07884	7.899723	-9	<.0001
origin	ND	-171.8758	19.31808	-8.9	<.0001
origin	NE	320.5601	89.64692	3.58	0.0003
origin	NJ	-113.0964	30.4998	-3.71	0.0002
origin	NV	290.05392	18.80194	15.43	<.0001
origin	NY	-315.9826	16.22136	-19.48	<.0001
origin	OH	18.71992	5.868384	3.19	0.0014
origin	OK	-80.42552	15.00878	-5.36	<.0001
origin	OR	88.164294	18.44315	4.78	<.0001
origin	PA	-173.0522	9.079137	-19.06	<.0001
origin	SC	143.73132	10.69946	13.43	<.0001
origin	SD	74.642339	10.0615	7.42	<.0001
origin	TN	79.613316	8.266336	9.63	<.0001
origin	UT	-336.9918	81.22821	-4.15	<.0001
origin	WA	-201.2081	14.64187	-13.74	<.0001
origin	WI	216.10666	5.924735	36.48	<.0001
Dest	AL	-35.88118	9.369405	-3.83	0.0001
Dest	AR	-80.66205	10.34488	-7.8	<.0001
Dest	AZ	-55.76328	10.37204	-5.38	<.0001
Dest	CA	-340.0643	5.977577	-56.89	<.0001
Dest	CO	470.58218	10.23278	45.99	<.0001
Dest	CT	624.86196	14.32107	43.63	<.0001
Dest	DE	227.15393	14.1267	16.08	<.0001
Dest	FL	491.90678	6.34121	77.57	<.0001
Dest	GA	-80.56868	8.311393	-9.69	<.0001
Dest	IA	-286.9609	5.843822	-49.1	<.0001
Dest	ID	360.60679	16.65502	21.65	<.0001
Dest	IL	-228.3654	6.354891	-35.94	<.0001
Dest	IN	-230.0248	7.684774	-29.93	<.0001
Dest	KS	-90.73351	10.91203	-8.31	<.0001
Dest	KY	-101.0306	9.30545	-10.86	<.0001

Dest	LA	74.080194	9.112918	8.13	<.0001
Dest	MA	630.98316	11.35267	55.58	<.0001
Dest	MD	304.98278	9.648878	31.61	<.0001
Dest	ME	809.2627	11.97841	67.56	<.0001
Dest	MI	-139.6004	6.75837	-20.66	<.0001
Dest	MN	-186.1691	6.161588	-30.21	<.0001
Dest	MO	-177.3952	8.612153	-20.6	<.0001
Dest	MS	-95.91002	9.99214	-9.6	<.0001
Dest	MT	579.73902	13.5929	42.65	<.0001
Dest	NC	-92.8968	7.729131	-12.02	<.0001
Dest	ND	148.15691	9.395576	15.77	<.0001
Dest	NE	-132.3405	13.60958	-9.72	<.0001
Dest	NH	758.92071	15.93853	47.62	<.0001
Dest	NJ	378.68021	9.35495	40.48	<.0001
Dest	NM	392.02198	14.37627	27.27	<.0001
Dest	NV	130.87091	24.97924	5.24	<.0001
Dest	NY	491.90065	7.422986	66.27	<.0001
Dest	OH	-73.88423	5.971924	-12.37	<.0001
Dest	OK	-80.66324	7.914288	-10.19	<.0001
Dest	OR	333.09867	10.84196	30.72	<.0001
Dest	PA	258.25075	5.833363	44.27	<.0001
Dest	RI	652.03665	28.20756	23.12	<.0001
Dest	SD	-65.52486	14.7939	-4.43	<.0001
Dest	TN	-161.9972	8.649579	-18.73	<.0001
Dest	WY	561.17334	26.09882	21.5	<.0001
Dest	UT	287.18339	14.89212	19.28	<.0001
Dest	VA	173.37447	8.884018	19.52	<.0001
Dest	VT	691.41658	16.457	42.01	<.0001
Dest	WA	227.56289	9.441534	24.1	<.0001
Dest	WI	-321.4685	6.177072	-52.04	<.0001
Dest	WV	60.30227	16.41251	3.67	0.0002

A6. Pricing model – Greater than 1000 miles & Less than 1000 miles run separately

Term	> 1000 Miles				< = 1000 miles			
	Estimate	Std Error	t Ratio	Prob> t	Estimate	Std Error	t Ratio	Prob> t
Intercept	-1465.306	58.39607	-25.09	<.0001	-1290.49	22.96911	-56.18	<.0001
soc_>=100	-81.59851	15.61465	-5.23	<.0001	-133.8448	5.604241	-23.88	<.0001
soc_50_100	-251.2481	12.61376	-19.92	<.0001	-124.8794	4.888936	-25.54	<.0001
miles	1.4195329	0.008297	171.09	<.0001	1.6509869	0.005776	285.81	<.0001
Add_picks 1	184.49982	16.57886	11.13	<.0001	145.12606	5.212459	27.84	<.0001
Add_picks 2	91.230097	37.32359	2.44	0.0145	173.52376	12.81675	13.54	<.0001
Add_picks>= 3	132.01461	179.2416	0.74	0.4614	385.40228	26.47623	14.56	<.0001
Add_drops 1	308.46355	20.77763	14.85	<.0001	231.06969	6.693663	34.52	<.0001
Add_drops 2	354.61983	21.63465	16.39	<.0001	238.62364	7.177167	33.25	<.0001
Add_drops>= 3	391.94416	21.96579	17.84	<.0001	228.99524	7.542006	30.36	<.0001
continuous move_indicator	-433.5068	16.48778	-26.29	<.0001	-177.6702	6.208223	-28.62	<.0001
consecutive drops30	-128.8496	6.460404	-19.94	<.0001	-22.88378	1.66277	-13.76	<.0001
consecutive picks30	-156.1982	24.13821	-6.47	<.0001	-37.3707	6.386843	-5.85	<.0001
leadtimeh0_16	31.672107	6.718323	4.71	<.0001	-12.95443	2.605921	-4.97	<.0001
leadtime16_72	28.793564	5.030673	5.72	<.0001	-6.843029	1.991233	-3.44	0.0006
planned	41.069721	17.4551	2.35	0.0186	-22.01666	3.414207	-6.45	<.0001
out-of-route	-0.143818	0.014241	-10.1	<.0001	0.1298488	0.011524	11.27	<.0001
index	14.076667	0.420197	33.5	<.0001	10.914657	0.165802	65.83	<.0001

A7. Pricing model – OTD

Term	MSTL				Direct			
	Estimate	Std Error	ChiSquare	Prob> ChiSq	Estimate	Std Error	ChiSquare	Prob> ChiSq
Intercept	-1.75	0.010	30026	<.0001	-1.924	0.003	351352	<.0001
depth 2	0.227	0.024	84.7	<.0001	0.115	0.007	270.82	<.0001
depth 3	0.465	4.44E-02	109.3	<.0001	0.206	1.20E-02	294	<.0001
depth 3+	0.484	0.024	413.65	<.0001	0.257	0.0075	1168	<.0001

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