# A Study of Shipper Performance in the Less-Than-Truckload Market

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## Abstract

When it comes to LTL shipping, it can be tough for shippers to get the performance that they expect due to the makeup of LTL networks. On-time performance is dependent on many more factors than in full truckload shipping. Performance often comes down to attributes of the shipment such as size and weight and also attributes of the geographical shipment volume. It is critical for shippers to understand these attributes and how they contribute to on-time performance of their own shipments. Through quantitative and qualitative analysis, this capstone details the shipment, shipper, and geographical characteristics that impact on-time performance of LTL shipments. Data from 33 shippers over a period of nearly two years was provided by C.H. Robinson and TMC (a division of CHR). This data was evaluated through a mix of regression and segmentation methods, as well as through qualitative understanding of the industry and economic landscape. The modeling and analysis here within describe the attributes of high performing shipments and provides guidance for shippers as to how to strive for the best performance. We found that shipment size, transit length, and destination shipment volume are among the largest drivers of on-time performance. Although on-time pick up and on-time delivery share some common significant drivers, significant drivers are not all the same for both. This report dives into further detail to help shippers understand the drivers what they can do to manage expectations and performance of their LTL shipments.

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I wish to thank my parents Michele and Dan for their endless support. I especially want to thank Kelley for her love, encouragement, and patience over the past year. I also want to thank Ben; it has been a pleasure to work together. Without all of you this report would not have been possible.

- *Chris Rallis*

For those all who care.

- *Ben Yin*

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# 1. Introduction

The trucking industry is worth nearly $600 billion in the United States (A.T. Kearney 2017). It represents over 3% of the country's gross domestic product and is the primary mode of transportation for goods. The trucking industry is segmented into full truckload (TL), less-than-truckload (LTL), and private/dedicated. Full truckload denotes point-to-point carriers which, as the name implies, ship full truckloads of product from an individual shipper. Conversely, less-than-truckload carriers deal with smaller shipments, typically ranging from 100 to 10,000 pounds, that are consolidated into one truck. Finally, private and dedicated fleets are owned or leased by a single shipper and, typically, only carry their own shipments.

LTL shipping networks are much different than those of truckload. Truckload carriers focus on point to point shipments; they pick up at the origin and drive directly to the destination where the entire trailer is unloaded. LTL, on the other hand, has many stops. It begins with a local pickup route where trucks pick up all the local shipments and bring those to a local terminal. At the terminal, also known as a consolidation center or breakbulk, shipments are organized and loaded into trailers based on destination. Next begins the line haul portion of the LTL shipment. In some cases, the shipments will travel directly to their destination terminal, but in many cases, shipments will need to go through one or more intermediary terminals where they are again sorted and routed based on destination. Once the shipments reach the appropriate destination terminal, they are delivered to their final destination via local trucks. Figure 1 shows the basic design of an LTL network. Importantly, fleets and terminals are privately owned by carriers, which makes LTL networks much more capital intensive. As opposed to truckload where most businesses are owner-operator and have on average three to five trucks. These features of LTL create barriers to entry limiting the number LTL carriers to around 120.

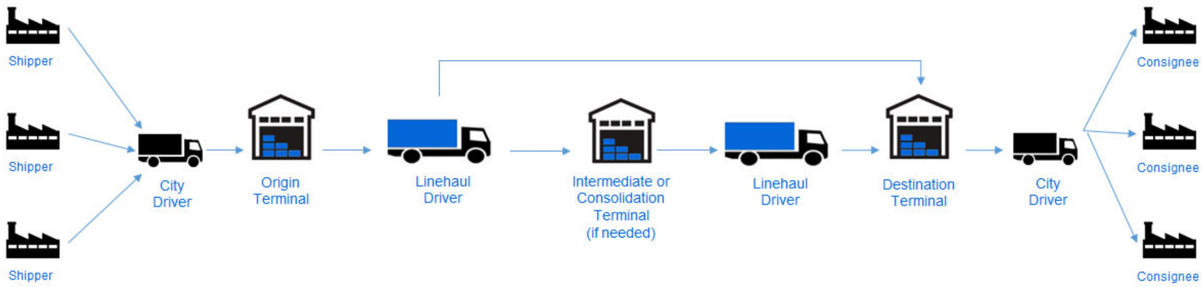



*Figure 1: LTL Network (LogisticsPlus 2017)*

Proportionally, TL and private shipping make up the majority of the trucking market, however, LTL still comprises $35 billion of the industry (Schulz 2017). This represents a large opportunity for shippers to ensure that they have optimized their LTL shipping strategies. Additionally, the LTL industry and shippers have come under pressure in recent years from what some are calling the "Amazon effect" (Lockridge 2017). The rapid growth of eCommerce has created an increasing emphasis on higher turnover through lower inventory levels and faster shipping. This has led to a shift from TL towards LTL-sized freight and parcel shipments being grouped for the line haul leg of delivery. However, capacity in the LTL market has remained largely unchanged. This is due to the carrier consolidation in the LTL industry that reduced the carrier number and the aforementioned barriers to entry that prevent new carriers entering the market.

This research was conducted with C.H. Robinson (CHR) and TMC. CHR, one of the world's largest third-party logistics providers, delivers a broad range of services to its over 113,000 customers. TMC is a division of CHR that provides support via its transportation management system and logistics process management. Together CHR and TMC provide customers with transportation management for all major segments of the trucking industry including truckload and LTL, at both a regional and national level.

This research focuses on the on-time performance of LTL shipments as well as what is realistic for shippers to expect from the performance of their LTL shipments and carriers. We analyzed attributes of shipments, origins and destinations, shippers, and carriers in order to understand which attributes impact the on-time performance of LTL shipments. Understanding these key performance drivers is critical as e-commerce continues to exert pressure on the industry to meet increasingly tight delivery standards.

For this research, we define on-time performance, or level of service, as on-time pickup and on-time delivery. With this we defined a perfect shipment as one that was both picked up and dropped off on-time. Industry performance metrics are discussed further in the literature review. The goal is to quantify statistically important attributes and their impact on performance. We will couple this with qualitative analysis to understand how these variables are influenced by the industry and other macro factors. Finally, the results provided herein will offer shippers valuable insight on how to understand, manage, and optimize their LTL shipping strategies.

The remainder of this report is organized as follows. Chapter 2, Literature Review, will discuss the industry metrics and quantitative analysis techniques that we leveraged. Chapter 3, Methodology, dives into the dataset, its attributes, and how we handled it. Chapter 4, Modeling, details the quantitative modeling performed on the dataset. Chapter 5, Results, discusses the findings of the models qualitatively. Finally, Chapter 6, Discussion and Conclusion, expands upon our research findings with recommendations for LTL shippers and further discussion.

# 2. Literature Review

This review briefly discusses less-than-truckload (LTL) industry dynamics and performance metrics, the regression methods used, and the appropriateness of applying such methods to freight research.

## 2.1 LTL Industry Dynamics and Performance Metrics

Certain ongoing changes in LTL industry kept their momentum in 2018, with the biggest ones being limitation on capacity expansion, and concentrated revenue among the largest LTL carriers (Schulz 2017). This contributed to a stronger negotiation power for carriers and potential higher prices for shippers. Therefore, the question of "How can shippers improve their LTL on-time performance?" stands out, as shippers can use this information for price negotiation and other internal management improvement purposes.

On-time performance is a widely accepted measurement in the freight industry, which consists of on-time pickup and on-time delivery. The measurement is especially meaningful from a shipper's perspective, considering the significant business impact being on-time has to supply chain management. Tardiness can cause ripple effects up and down supply chains, resulting in increased costs, stock out, lost sales and poor customer satisfaction.

## 2.2 Regression Methodology Used

Binary logistic regression has been a very popular technique in social science research for many years. It identifies independent variables ($X_k$) that have statistically significant correlation with a dependent binary variable ($Y$) being studied. Usually $Y$ equals either 1, or 0.

The logistic regression equation is:

$$Ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

where $P$ is the probability of $Y$=1.

A key factor to regression models is the selection of explanatory variables. Harrell (2015) suggests that if a p-value-based method (such as stepwise regression) should be used, a backward method is desired. Backward stepwise method begins with all the explanatory variables, and then iteratively removes the least useful ones, one-at-a-time. Another aspect of variable selection is to remove the multicollinearity among explanatory variables. Multicollinearity is a phenomenon where one predictor in a multiple regression model can be linearly predicted from the others with a substantial degree of accuracy. In the case of multicollinearity, the coefficient estimate of each independent variable may change erratically in response to slight changes in the dataset. To identify and reduce the impact of multicollinearity, principle component analysis or a correlation matrix can be used.

## 2.3 Appropriateness of Using the Methodologies in Freight Research

Logistic regression has extensive use in the research of freight industry and its validity in this area has been supported by numerous research. For example, Chen and Tsai (2016) used logistic regression to study the correlation between acceptance ratio and other factors in multi-stop carrier settings. Bleggi and Zhou (2017) employed logistic regression in a full truckload dataset to study the influencing predictors to on-time performance.

# 3. Data Overview

This chapter provides an overview of the dataset. It comprises three sections, Data Cleaning and Manipulation, Data Segmentation, and Description of Data. Data cleaning and manipulation details the erroneous data that was removed and how certain data features were manipulated to provide basis for further analysis. Data mapping and analysis provides an explanation for initial findings in the dataset as well as how variables were decided upon and their interactions. Finally, modeling describes the strategies used to evaluate the dataset from a regression and clustering perspective.

## 3.1 Data Cleaning and Manipulation

The dataset provided by TMC included data from LTL shippers for nearly two years from January 2016 to October 2017. The first task was to ensure that all records were true LTL. This was performed jointly with the team at C.H. Robinson and TMC to leverage their insight and professional expertise. Records that were excluded as a result of this were shippers who typically shipped truckload, which was quantified as any shipper that had less than a hundred instances of LTL shipments. Furthermore, the decision was made to limit the data to carriers that had performed at least 5,000 shipments over the three years to ensure there was enough carrier data to draw solid conclusions. It was also decided to limit shipments to those within the contiguous 48 states since too few shipments occurred outside this region to have meaningful data.

Cleaning was performed on the dataset to ensure all values were consistent, and any typographical errors were fixed or eliminated. Cleaning for consistency included normalizing all date fields and eliminating time stamps, since very few records were time stamped and LTL shipping is typically appointed to the day. It also included evaluating and deleting or fixing all geographical elements such as addresses and zip codes to be consistent to avoid errors in future analysis. The final part of cleaning was to remove any extreme outliers in the data in terms of impossible weight, distance, and duration values.

Once the data was clean, certain variables were manipulated to make future analysis easier. Since the primary objective was to evaluate shipment performance on the basis of on-time pickup (OTP), on-time delivery (OTD), and on-time overall, three new columns were created that turned this performance into binary variables. A “1” in any of the aforementioned variable columns meant that shipment stop was on-time, while a “0” meant it was late. On-time overall was a function of OTP and OTD; if either stop was late then the overall status was late or, in other words, not perfect. Conversely, a perfect shipment meant it was picked up and dropped off on time. This was not straightforward, as evaluation dates had to be assigned to assess pickup and drop-off dates. The logic for evaluation dates was that it would be equal to the scheduled date; if scheduled date was not populated then requested date was used. Actual arrived dates were then compared to the evaluation dates to determine on-time performance. The formulas for the evaluation dates and on-time calculations are as follows:

*Evaluation Date = Scheduled Date if populated, o.w. Requested Date*

*On-Time Pickup/Delivery = Actual Arrived Date ≤ Evaluation Date*

Binary flags were also created for other descriptive variables including whether a shipment contains hazardous material, employed brokerage, or encountered assessorial charges. These flags were created to easily visualize any applicable trends, which were then quantified and explained in the following Data Analysis and Results sections.

## 3.2 Data Segmentation

While most companies manage both their inbound, outbound, and transfer logistics, this analysis is focused on the outbound segment. We chose to focus here, because shippers typically have greater control of their outbound logistics. With inbound, there are many more factors out of the shipper's control that can affect on-time performance. Although this report is focused on outbound, shippers should still give attention to inbound and transfer logistics to understand how they differ and how to uniquely manage performance for each segment.

To achieve this analysis, we first segmented the shipment dataset into outbound, inbound, and transfer. Defined as:

- *Outbound – shipments <u>from</u> the shipper to a third party (customer, etc.) – 64% of the data*
- *Inbound – shipments <u>to</u> the shipper from a third party (supplier, etc.) – 34% of the data*
- *Transfer – intra-company shipments where origin and destination are both controlled by the shipper – 2% of the data*

The final segmentation that was performed was to extract all records from one particular shipper out of the transactional data. We, along with the team at C.H. Robinson and TMC, decided to do this because the shipper constituted nearly half of the total records and, therefore, would exhibit a large influence on the data.

## 3.3 Description of the Data

This section serves to describe the dataset from the perspective of overall network, shippers and their business groups, verticals, carriers, and geographical locations. Over the three years, and after the data cleansing, there were 947,221 outbound shipments from 33 shippers, which were handled by 26 carriers.

Overall network performance averaged 91% for on-time pickup and 86% for on-time delivery. There was a significant performance improvement in the spring of 2016. However, this was followed by a decline in on-time delivery during the winter of 2016 as well as in September 2017. Total load counts steadily increased during 2016 and two large shippers drove the steep increase from August to October 2016. However, load counts showed signs of tapering off during 2017. This is captured in Figure 2.

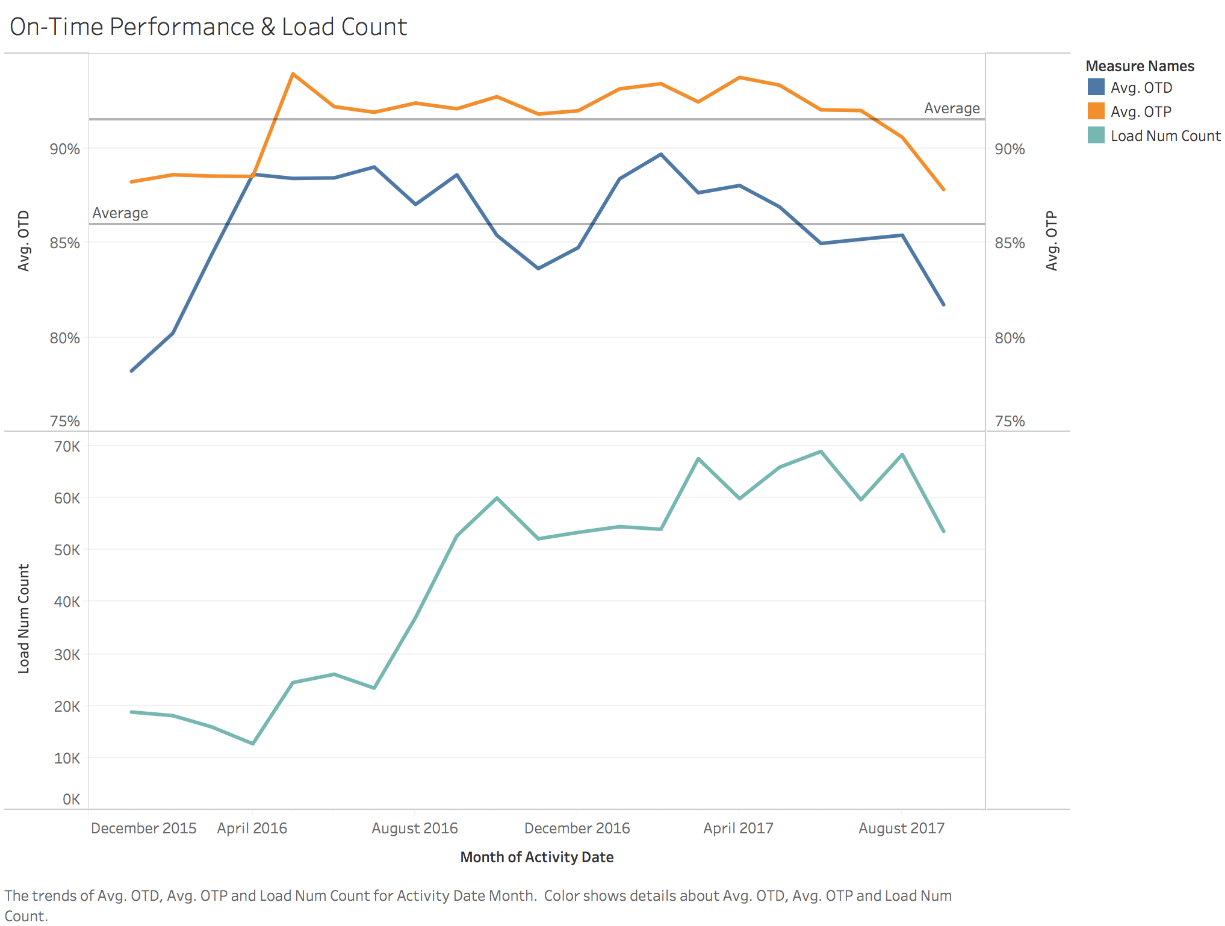
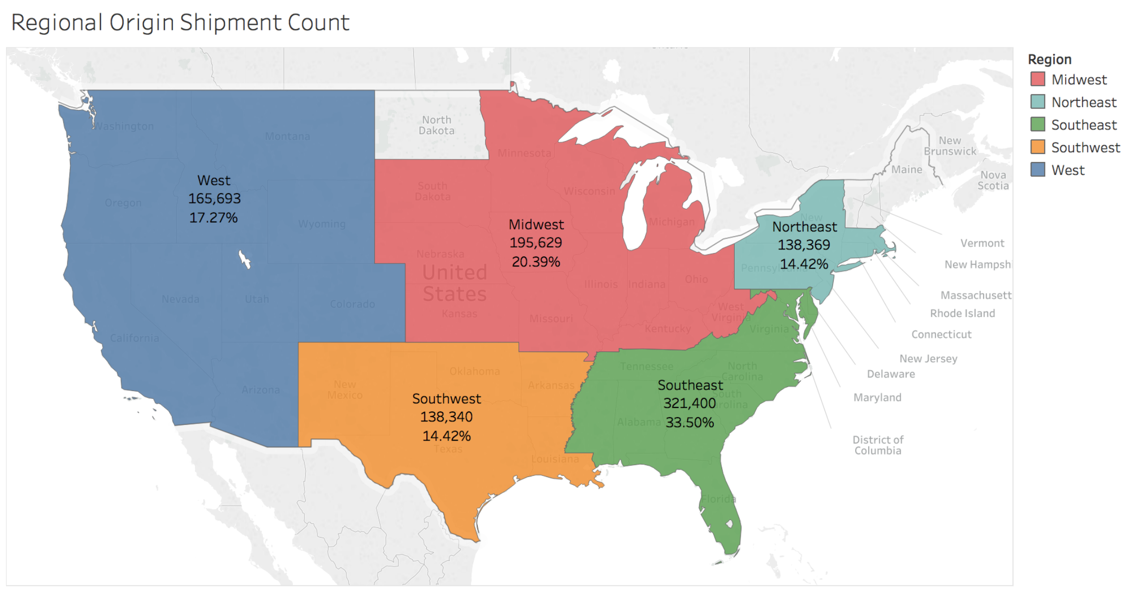


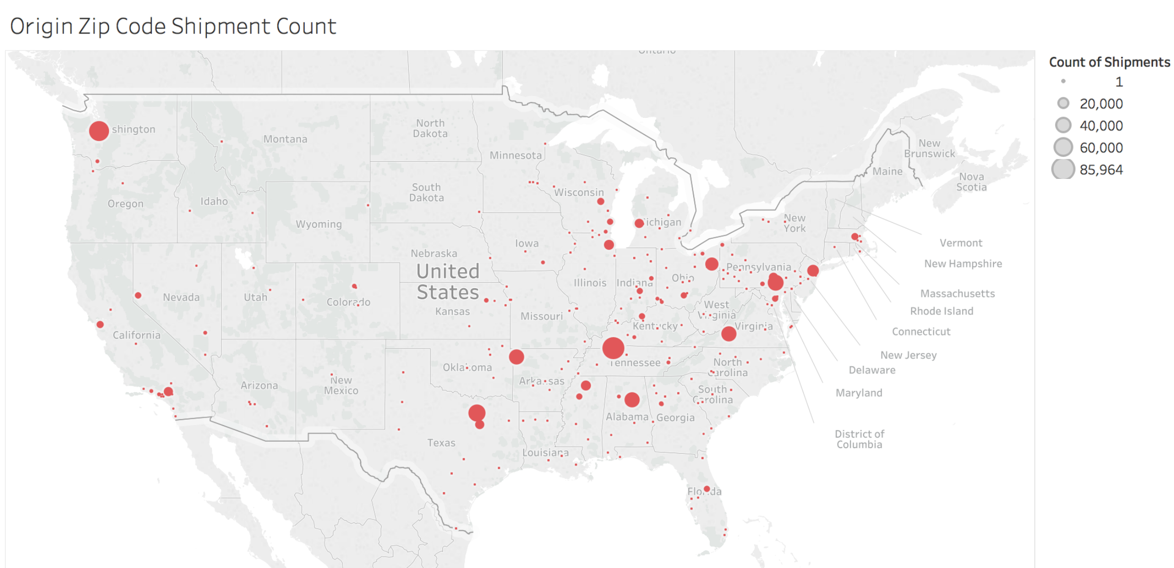

*Figure 2: On-Time Performance & Load Count*

Geographically, a third of all shipments originate in the Southeast, followed by a fifth of shipments coming from the Midwest. The rest of the regions make up the remaining with nearly equal parts as seen in the Figure 3 below. When we drill down to the state level, it can be seen that the vast majority of shipments originate from major cities (Figure 4).




Map based on Longitude (generated) and Latitude (generated). Color shows details about Origin State (group). The marks are labeled by Origin State (group), Load Num Count and % of Total Load Num Count. The data is filtered on Activity Date, which ranges from 1/1/2016 to 9/29/2017.

*Figure 3: Regional Origin Shipment Count*

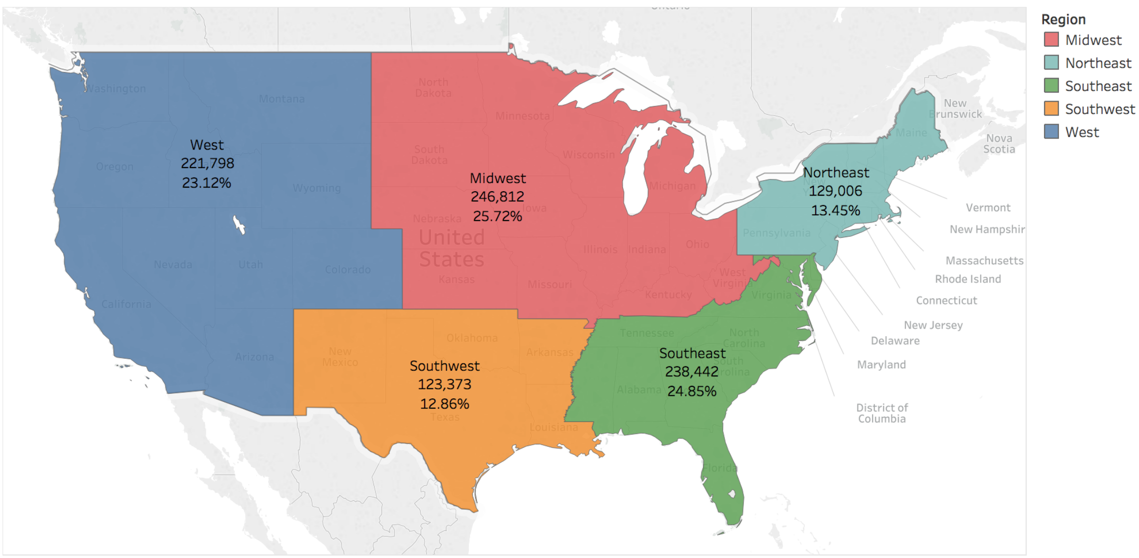



Map based on Longitude (generated) and Latitude (generated). Size shows Load Num Count. Details are shown for Company Code and Origin Zip. The data is filtered on Activity Date, which ranges from 1/1/2016 to 9/29/2017.

*Figure 4: 3-Digit Origin Zip Code Shipment Count*

Destinations are far more spread out, but the Southeast and Midwest still receive half of the shipments. At a state level we again see that most shipments are destined for major cities, but with a much greater spread than we saw for origins.

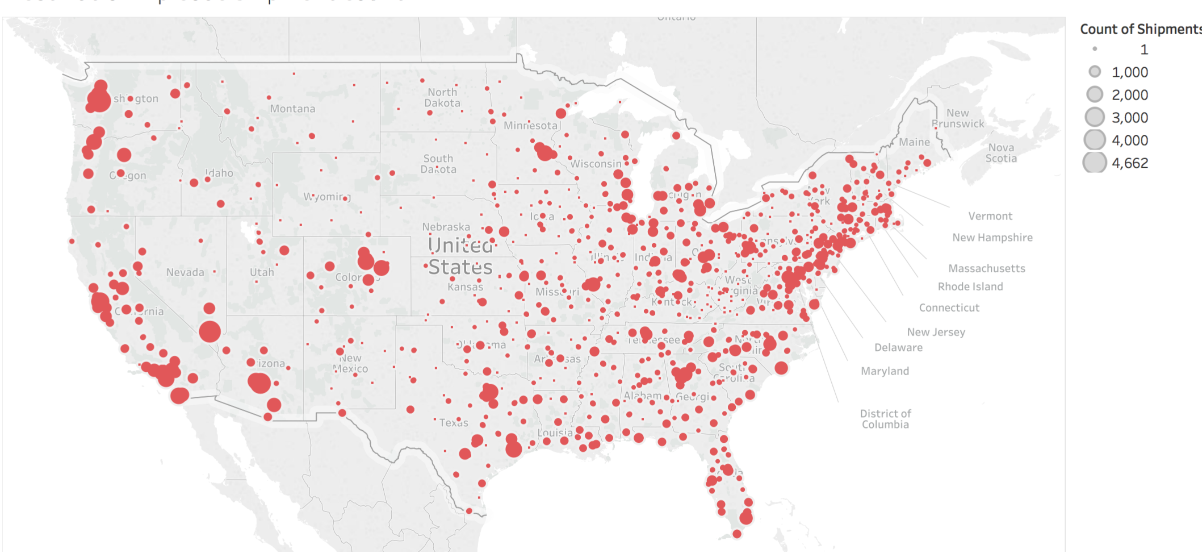
Regional Destination Shipment Count




Map based on Longitude (generated) and Latitude (generated). Color shows details about Destination State (group). The marks are labeled by Destination State (group), Load Num Count and % of Total Load Num Count. The data is filtered on Activity Date, which ranges from 1/1/2016 to 9/29/2017.

*Figure 5: Regional Destination Shipment Count*

Destination Zip Code Shipment Count




Map based on Longitude (generated) and Latitude (generated). Size shows Load Num Count. Details are shown for Company Code and Destination Zip. The data is filtered on Activity Date, which ranges from 1/1/2016 to 9/29/2017.

*Figure 6: 3-Digit Zip Code Destination Shipment Count*

The 33 shippers (firms) operate in unique ways and have a wide range of characteristics. These can be seen in Table 1. While shippers experience a broad range of on-time performance, the median of 95% for on-time pickup shows that most shippers have minimal issues getting shipments out the door. However, the median for on-time delivery is considerably lower at 83%. Understandably, there are many opportunities and reasons for a shipment to be delayed in transit; these will be discussed in Chapter 4. In terms of total shipment volume, two shippers account for 56% of the total shipment count. These two shippers vary greatly in their attributes, however the one thing that they have in common is that their shipment data (pallets; pieces; weight; cube volume) is much more complete in comparison to many smaller shippers. Additionally, these large shippers experience significantly higher (13% OTP; 17% OTD) performance than smaller shippers from regional carriers.

*Table 1: Shipper Attribute Summary*

| Firm | Load Num Count | On-Time Pick Up | On-Time Delivery | Perfect Shipment | Median Shipment Weight | Median Published Transit Days | # Business Units | # Shipping Origins | # Shipping Destinations | # Carriers Used |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4,804 | 88.7% | 89.3% | 79.4% | 5,132 | 1 | 1 | 7 | 543 | 11 |
| 2 | 8,586 | 97.3% | 82.3% | 81.3% | 275 | 2 | 4 | 9 | 2,621 | 10 |
| 3 | 639 | 98.3% | 90.8% | 89.8% | 692 | 2 | 1 | 3 | 263 | 3 |
| 4 | 367 | 98.4% | 92.1% | 90.7% | 5,000 | 2 | 2 | 3 | 182 | 2 |
| 5 | 19,333 | 73.2% | 83.4% | 60.6% | 361 | 2 | 2 | 5 | 1,107 | 6 |
| 6 | 450 | 93.1% | 72.2% | 70.7% | 1,250 | 1 | 1 | 8 | 127 | 5 |
| 7 | 463 | 95.9% | 80.1% | 79.7% | 4,950 | 1 | 1 | 1 | 117 | 2 |
| 8 | 111 | 99.1% | 88.3% | 87.4% | 4,140 | 2 | 2 | 2 | 52 | 2 |
| 9 | 211 | 95.3% | 98.1% | 93.8% | 5,436 | 2 | 1 | 2 | 103 | 7 |
| 10 | 38,719 | 41.9% | 56.3% | 28.6% | 417 | 2 | 1 | 1 | 4,630 | 11 |
| 11 | 7,324 | 90.5% | 55.7% | 53.2% | 1,545 | 1 | 7 | 19 | 3,179 | 6 |
| 12 | 723 | 96.5% | 91.8% | 88.9% | 4,369 | 2 | 2 | 2 | 222 | 5 |
| 13 | 16,239 | 90.2% | 72.2% | 66.0% | 2,169 | 2 | 2 | 66 | 5,760 | 12 |
| 14 | 67,275 | 82.8% | 91.0% | 76.5% | 287 | 2 | 10 | 30 | 13,811 | 8 |
| 15 | 41,159 | 80.8% | 80.5% | 67.9% | 354 | 2 | 2 | 3 | 15,568 | 8 |
| 16 | 6,370 | 79.3% | 41.6% | 38.3% | 236 | 4 | 3 | 14 | 3,918 | 4 |
| 17 | 14,929 | 94.0% | 97.3% | 91.8% | 1,164 | 2 | 2 | 4 | 479 | 5 |
| 18 | 9,291 | 87.2% | 79.2% | 71.9% | 733 | 2 | 2 | 7 | 2,445 | 10 |
| 19 | 21,707 | 85.8% | 82.0% | 73.1% | 435 | 2 | 1 | 32 | 8,451 | 6 |
| 20 | 3,486 | 99.4% | 94.0% | 93.6% | 351 | 2 | 1 | 2 | 260 | 6 |
| 21 | 292 | 97.6% | 97.3% | 95.2% | 1,991 | 2 | 2 | 2 | 58 | 10 |
| 22 | 6,161 | 100.0% | 99.1% | 99.1% | 1,000 | 2 | 2 | 12 | 360 | 5 |
| 23 | 2,937 | 62.0% | 49.8% | 36.8% | 188 | 3 | 1 | 3 | 1,983 | 5 |
| 24 | 169 | 96.4% | 93.5% | 93.5% | 714 | 1 | 2 | 3 | 78 | 3 |
| 25 | 381,837 | 97.2% | 91.6% | 90.6% | 709 | 1 | 4 | 14 | 14,706 | 4 |
| 26 | 23,653 | 92.3% | 90.0% | 85.4% | 281 | 2 | 2 | 4 | 4,920 | 3 |
| 27 | 13,695 | 96.9% | 79.5% | 78.2% | 638 | 2 | 2 | 24 | 1,412 | 7 |
| 28 | 48,282 | 94.5% | 82.4% | 80.8% | 312 | 2 | 6 | 7 | 2,628 | 1 |
| 29 | 15,709 | 98.7% | 83.9% | 83.5% | 1,178 | 1 | 3 | 10 | 2,860 | 10 |
| 30 | 150,145 | 99.8% | 94.2% | 94.1% | 959 | 1 | 3 | 19 | 5,405 | 14 |
| 31 | 5,759 | 98.0% | 83.5% | 82.2% | 1,146 | 2 | 5 | 4 | 1,513 | 5 |
| 32 | 448 | 99.8% | 96.0% | 95.8% | 2,565 | 1 | 3 | 6 | 237 | 4 |
| 33 | 35,948 | 92.9% | 52.3% | 51.9% | 68 | 1 | 3 | 105 | 6,092 | 13 |
| **Median** | **7,324** | **95.3%** | **83.9%** | **81.3%** | **733** | **2** | **2** | **6** | **1,513** | **6** |

Table 2 shows the correlation matrix of key variables at the shipper level for on-time performance, shipment weight, and published transit days. As expected on-time pickup is strongly and positively correlated to on-time delivery which, in turn, is strongly and positively correlated to perfect shipment. Weight is also positively correlated to on-time performance. However, it will be discussed later that there are high levels of variance when it comes to weight.

Finally, published transit days is negatively correlated to on-time performance. This reaffirms the industry belief that longer shipments will perform worse than shorter shipments. What surprised us the most from this correlation was that the number of shipments does not have a significant correlation with on-time performance. This shows that small and large shippers can both achieve high levels of performance.

*Table 2: Shipper Level Correlation Matrix*

| | *# Shipments* | *On-Time Pick Up* | *On-Time Delivery* | *Perfect Shipment* | *Median Shipment Weight* | *Median Published Transit Days* |
|---|---|---|---|---|---|---|
| Load Num Count | 1 | | | | | |
| On-Time Pick Up | 0.04 | 1 | | | | |
| On-Time Delivery | 0.11 | 0.61 | 1 | | | |
| Perfect Shipment | 0.10 | 0.83 | 0.94 | 1 | | |
| Median Shipment Weight | -0.21 | 0.29 | 0.33 | 0.34 | 1 | |
| Median Published Transit Days | -0.26 | -0.38 | -0.32 | -0.36 | -0.22 | 1 |

Out of the 33 shippers, 24 have more than one business unit. Most shippers in the dataset have one to three business units, however a few have more (max 10). We ran a correlation matrix at the business unit level and found nearly identical performance showing that business units have similar attributes and performance drivers within their respective firm.

*Table 3: Business Unit Level Correlation Matrix*

| | *# Shipments* | *Avg. OTP* | *Avg. OTD* | *Avg. On Time* | *Median Reference Weight* | *Median SMC Transit Days* |
|---|---|---|---|---|---|---|
| # Shipments | 1 | | | | | |
| Avg. OTP | 0.06 | 1 | | | | |
| Avg. OTD | 0.10 | 0.45 | 1 | | | |
| Avg. On Time | 0.11 | 0.65 | 0.94 | 1 | | |
| Median Reference Weight | -0.15 | 0.18 | 0.03 | 0.08 | 1 | |
| Median SMC Transit Days | -0.15 | -0.24 | -0.15 | -0.23 | -0.01 | 1 |

# 4. Data Modeling

This chapter examines the modeling and quantitative analysis performed on the dataset to understand factors affecting on-time pickup and on-time delivery. We identified 11 potential variables defined in Table 4. Modeling was separated by pickup and delivery. On-time pickup is the dependent variable in the pickup study and is considered an independent variable in the on-time delivery study.

*Table 4: Modeling Variable Definitions*

| # | Variable Name | Denotation | Data Type | Definition |
|---|---|---|---|---|
| 1 | OTD | X1 | Binary | On Time Delivery; 0 -> Not on time; 1 -> On time. |
| 2 | OTP | X2 | Binary | On Time Pick Up; 0 -> Not on time; 1 -> On time. |
| 3 | Rate | X3 | Continuous | Total amount paid on the load (Including LH, FSC, Accessorials) |
| 4 | SMC Transit Days | X4 | Continuous | Carrier published transit days for the lane |
| 5 | Miles | X5 | Continuous | Mileage of the shipment |
| 6 | Delivery Distance | X6 | Continuous | Mileage between the delivery point and delivery terminal |
| 7 | Origin Distance | X7 | Continuous | Mileage between the origin point and origin terminal |
| 8 | Weight | X8 | Continuous | Actual weight of Shipment |
| 9 | Number of Pallets | X9 | Continuous | Actual count of Pallets |
| 10 | Ord Pallet Positions | X10 | Continuous | Planned version of the count of pallet |
| 11 | Volume | X11 | Continuous | Cubic feet of the shipment |
| 12 | Fuel | X12 | Continuous | Fuel surcharge |

**Note: SMC Transit Days represents published transit days provided by carriers to SMC and are herein referred to as published transit days.*

Due to data availability we ran three models in parallel. These models were performed on the full dataset described earlier as well as a constrained dataset. The constrained dataset was made up of only shipment records that contained non-zero values for actual pallets, ordered pallet positions, cube volume, distance from origin terminal, and distance from destination terminal. The constrained dataset contains around one-fourth of the shipment records of the full dataset. The three models were performed for both on-time pickup and on-time delivery resulting in different significant variables for each. For these models we have defined two classes of variables:

- *Normal Variables – Rate, Miles, Published (SMC) Transit Days, and Shipment Weight*
- *Constrained Variables – Actual Pallets, Ordered Pallet Positions, Cubic Volume, Distance to Origin Terminal, Distance to Destination Terminal*

The models are defined as:

- *Model 1: Normal Variables on Full Dataset*
- *Model 2: Normal Variables on Constrained Dataset*
- *Model 3: Normal Variables + Constrained Variables on Constrained Dataset*

Performing the analysis like this allows us to verify the significance of any normal variables on both datasets before adding the constrained variables to the model.

## 4.1 Modeling On-Time Pickup in Outbound Dataset

This section discusses on-time pickup (OTP) performance and the influential factors associated with this metric. Typically, shippers are more focused on getting shipments delivered to their customers on-time, but, as we showed in the earlier correlation matrices, on-time pickup has a large influence on delivery and can also impact a shipper's upstream supply chain.

On-time pickup performance was analyzed at the individual shipment level as well as at the location level to understand any location specific factors. These will be discussed in the following sub-sections. As mentioned earlier, pickup performance exceeded that of delivery. On-time pickup averaged 91% over the two years.

### 4.1.2 Modeling OTP on TMC Shipment Dataset

Before performing the aforementioned three parallel models, we evaluated the correlation matrix for the full and constrained shipment data. This was done to remove any variables with statistical and logical collinearity. The correlation matrices are shown in Figures 7 and 8.

From the normal variables on full shipment data matrix (Figure 7) we can discern that miles and published transit days are highly correlated. This makes sense since they both represent how far a shipment is going (distance and time).

**Multivariate**

**Correlations**

| | Rate | Miles | SMC_Transit_Days | Reference_Weight |
|---|---|---|---|---|
| Rate | 1.0000 | 0.3155 | 0.2582 | 0.6579 |
| Miles | 0.3155 | 1.0000 | 0.7302 | -0.0201 |
| SMC_Transit_Days | 0.2582 | 0.7302 | 1.0000 | -0.0206 |
| Reference_Weight | 0.6579 | -0.0201 | -0.0206 | 1.0000 |

*Figure 7: Normal Variables / Full Data Correlation Matrix*

From the normal and constrained variables on constrained data correlation matrix we once again see that miles and published transit days are highly correlated. Additionally, actual pallets and ordered pallet positions are nearly perfectly correlated. This is likely because shippers do not assume stacking of pallets is possible when choosing how many pallet positions to order; they leave this up to the carrier.

**Multivariate**

**Correlations**

| | Rate | Miles | SMC_Transit_Days | Reference_Weight | # Pallets | # Ord Pal Pos | Volume |
|---|---|---|---|---|---|---|---|
| Rate | 1.0000 | 0.3404 | 0.3209 | 0.6811 | 0.6444 | 0.6692 | 0.1428 |
| Miles | 0.3404 | 1.0000 | 0.7984 | 0.0268 | 0.1336 | 0.1301 | 0.0631 |
| SMC_Transit_Days | 0.3209 | 0.7984 | 1.0000 | 0.0413 | 0.1118 | 0.1138 | 0.0347 |
| Reference_Weight | 0.6811 | 0.0268 | 0.0413 | 1.0000 | 0.6508 | 0.6893 | 0.1099 |
| # Pallets | 0.6444 | 0.1336 | 0.1118 | 0.6508 | 1.0000 | 0.9413 | 0.2153 |
| # Ord Pal Pos | 0.6692 | 0.1301 | 0.1138 | 0.6893 | 0.9413 | 1.0000 | 0.2302 |
| Volume | 0.1428 | 0.0631 | 0.0347 | 0.1099 | 0.2153 | 0.2302 | 1.0000 |

*Figure 8: Normal + Constrained Variables / Constrained Data Correlation Matrix*

From the correlation matrices we chose to remove miles from future modeling due to the high correlation with published transit days. From our discussions with CHR and TMC, we are confident that published transit days takes into account mileage as well as carrier network and, therefore, captures more data than miles alone. We also chose to remove ordered pallet positions due to the high correlation with actual pallets. Furthermore, distance to destination terminal was removed since this analysis is focused on pickup. Finally, we chose to eliminate rate. This is because it is driven primarily by distance (captured by published transit days) and weight.

Another modification we chose to make was to weight. As seen in Figure 9, performance appears to increase from low weights up to around 650 pounds, then flattens off, before becoming very erratic at higher weights. Due to this we chose to create three weight classes to evaluate in the models. However, a huge amount of variation can be seen in the higher weights, which will be discussed later.

- *Low: shipment weights ≤ 650 lbs. (34% of shipments)*
- *Mid: 650 lbs. < shipment weights ≤ 5,000 lbs. (64% of shipments)*
- *High: shipment weights > 5,000 lbs. (2% of shipments)*

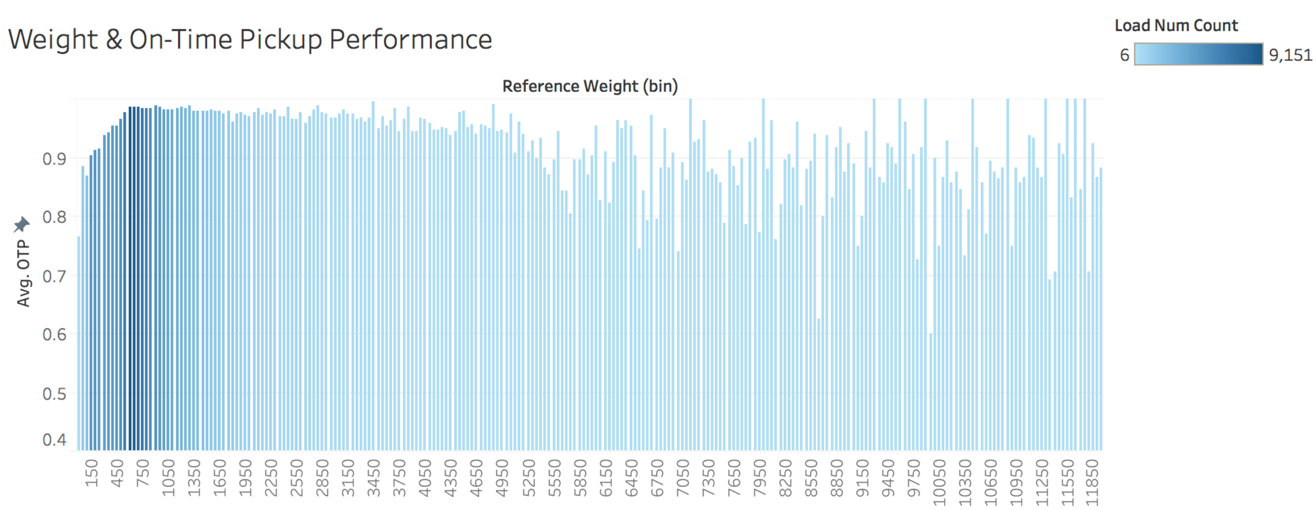



*Figure 9: Histogram of Weight and On-Time Pickup Performance (based on constrained data)*

Results of the three logistic regression models are shown in Table 5. In model 3, cube volume was shown to not be significant based on the p-value. From these results, cube volume was removed and a final model (M3*) was run.

*Table 5: On-Time Pickup Modeling Results*

| | M1 R^2: 2.77% | | M2 R^2: 3.09% | | M3 R^2: 6.07% | | M3* R^2: 6.26% | |
|---|---|---|---|---|---|---|---|---|
| **Term** | **Coefficient** | **P-Value** | **Coefficient** | **P-Value** | **Coefficient** | **P-Value** | **Coefficient** | **P-Value** |
| Intercept | 2.5511 | <0.0001 | 3.1843 | <0.0001 | 3.0002 | <0.0001 | 2.9531 | <0.0001 |
| SMC Transit Days (X4) | -0.2717 | <0.0001 | -0.2295 | <0.0001 | -0.1413 | <0.0001 | -0.1379 | <0.0001 |
| Low Weight (X8a) | 0.0004 | <0.0001 | 0.0007 | <0.0001 | 0.0011 | <0.0001 | 0.0013 | <0.0001 |
| Mid Weight (X8b) | 0.0005 | <0.0001 | 0.0007 | <0.0001 | 0.0011 | <0.0001 | 0.0011 | <0.0001 |
| High Weight (X8c) | 0.0001 | <0.0001 | -0.0001 | <0.0001 | 0.0003 | <0.0001 | 0.0003 | <0.0001 |
| Number of Pallets (X9) | N/A | N/A | N/A | N/A | -0.2499 | <0.0001 | -0.2515 | <0.0001 |
| Volume (X11) | N/A | N/A | N/A | N/A | -0.000001* | 0.9015 | N/A | N/A |
| Distance to Origin Terminal (X7) | N/A | N/A | N/A | N/A | 0.0103 | <0.0001 | -0.0103 | <0.0001 |

** Variable was not significant based on resulting p-value*

$$P = \frac{e^{2.9531-0.1379x_4+\ 0.0013x_{8a}+0.0011x_{8b}+0.0003x_{8c}\ -0.2515x_9-0.0103x_7}}{1+\ e^{2.9531-0.1379x_4+\ 0.0013x_{8a}+0.0011x_{8b}+0.0003x_{8c}\ -0.2515x_9-0.0103x_7}}$$

These models show, first and foremost, by their R^2 values that there is an immense amount of variation in the dataset. Nonetheless, published transit days, shipment weight, number of pallets, and distance to origin terminal are all statistically significant. These results will be discussed in more detail in the next chapter.

### 4.1.2 Modeling OTP Geographically

Origin codes represent unique shipping locations for shippers. Each origin code is associated with only one shipper and are located in a single 3-digit zip code. Performing regression modeling on these we hoped to understand if there was a locational impact on pickup performance. However, after analysis, only published transit days showed strong correlation to origin code on-time pickup performance. Since published transit days is more highly correlated at the shipment level as previously discussed we concluded that this is a significant variable of a shipment rather than the origin code. We hoped to find a density (number of shipments) relationship, as later discussed for OTD, but there was no statistical correlation. Figure 10 shows a map of pickup performance aggregated to the 3-digit zip code level. This map helps visualize what the analysis showed at the origin code level, that small and large shipping locations have good and poor average pickup performance. We will discuss potential reasons for this in the results section.

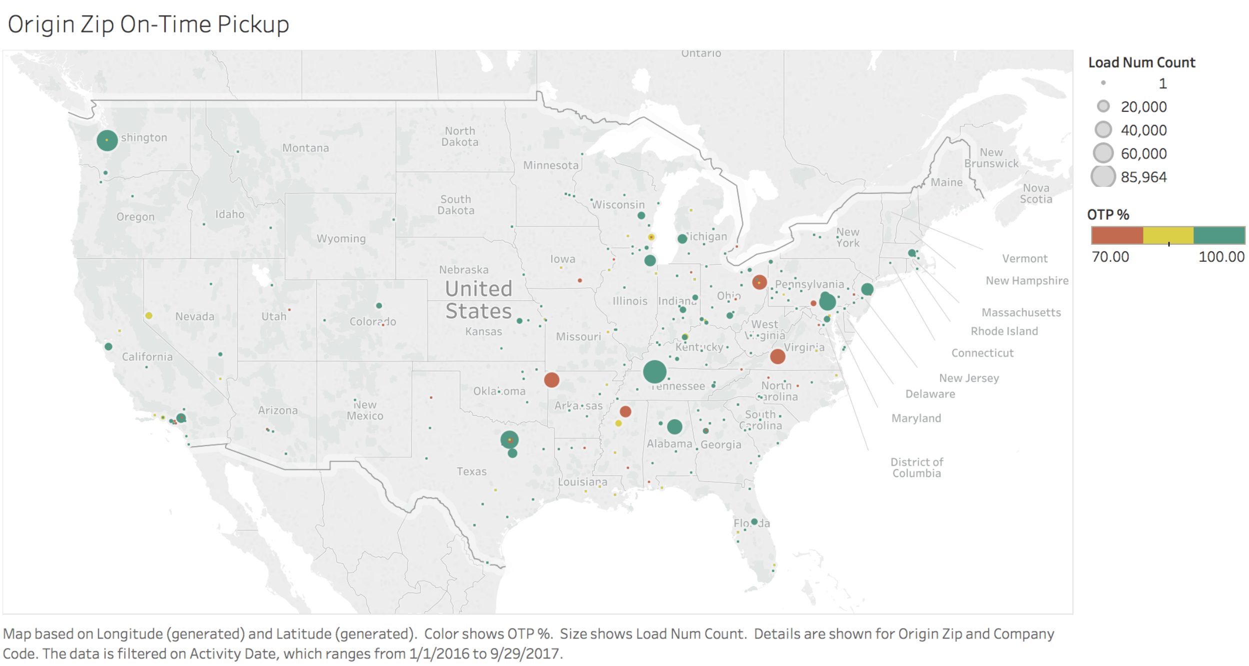



*Figure 10: 3-digit Origin Zip Code OTP Performance (Green: <90%, Yellow: 80-90%, Red: <80%)*

## 4.2 Modeling On-Time Delivery in Outbound Dataset

This section discusses the geographical analysis of on-time delivery (OTD), logistic regression analysis of OTD on business unit level, and lastly the segmentation of leader, middle and laggard business units.

The geographical analysis shows the performance of OTD regardless of shipper and carrier, followed by a correlation analysis to find the correlation between the count of shipment going to a region and that region's OTD performance. Regions are defined at the 3-digit zip code level. The logistic regression was conducted to explore significant factors to OTD on each shipment level in the full and constrained dataset. After significant factors were defined, the segmentation process divides all business units into leader, middle and laggard groups. It further analyzes how leaders perform differently to laggards on those significant factors and provides the basis of improvement suggestions for laggards.

### 4.2.1 OTD Geographical Analysis

We aggregated all the shipments based on their destination states and summarized the average OTD% and count of shipments, visualization in Appendix C. On the state level in the full dataset, the highest performing one achieved 92.67% (Vermont), compared to the lowest 75.4% (West Virginia). The majority of OTD% distribution lies in 80% – 88% interval. The possible gap between the results shown here and general industry knowledge is because of the definition of OTD. In this research OTD was measured on actual delivery date against schedule/ requested delivery date, which reflected shippers' perspective.

At the 3-digit zip code level, the on-time delivery ratio is more dispersed. The highest achieving zip code has 99.2% versus the lowest 39.4%, with a median OTD ratio of 83.4%. In addition, 9% of the 3-digit zip codes achieved above 90% OTD ratio, 60% of the zip codes fall into 80% to 90% OTD ratio interval. Around 6% of zip codes performed below 70% OTD ratio. Figure 11 shows the OTD performance of the zip codes on the map.

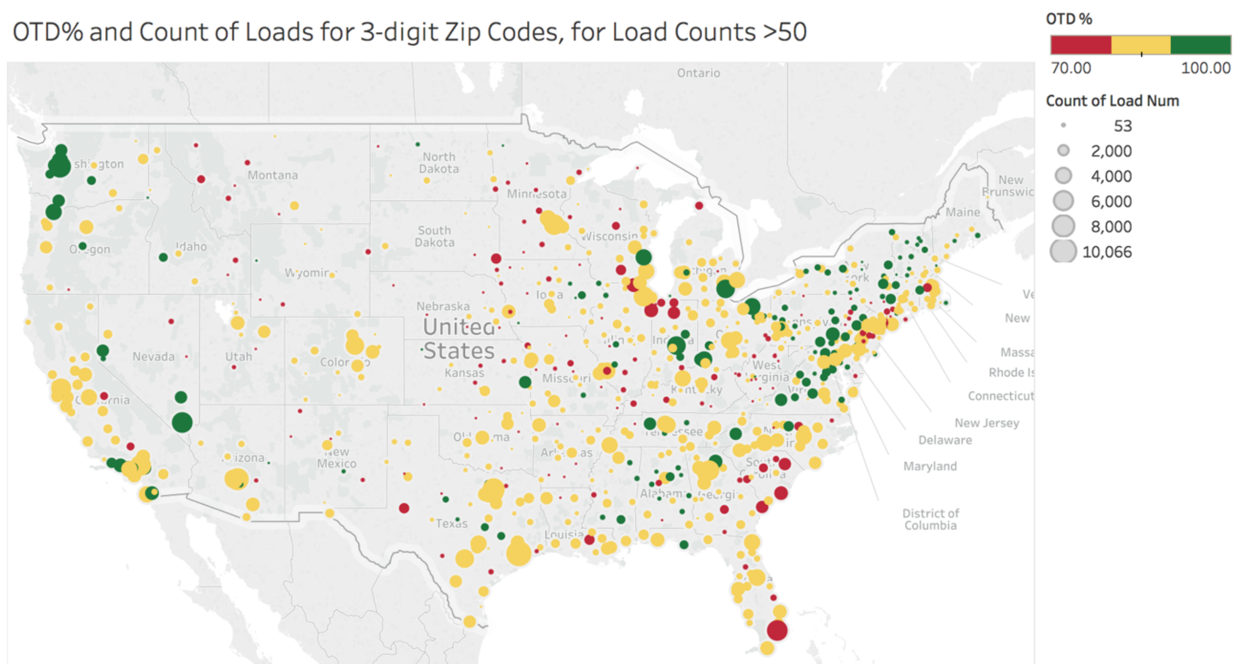



*Figure 11: OTD% and Count of Loads on 3-Digit Zip Codes*

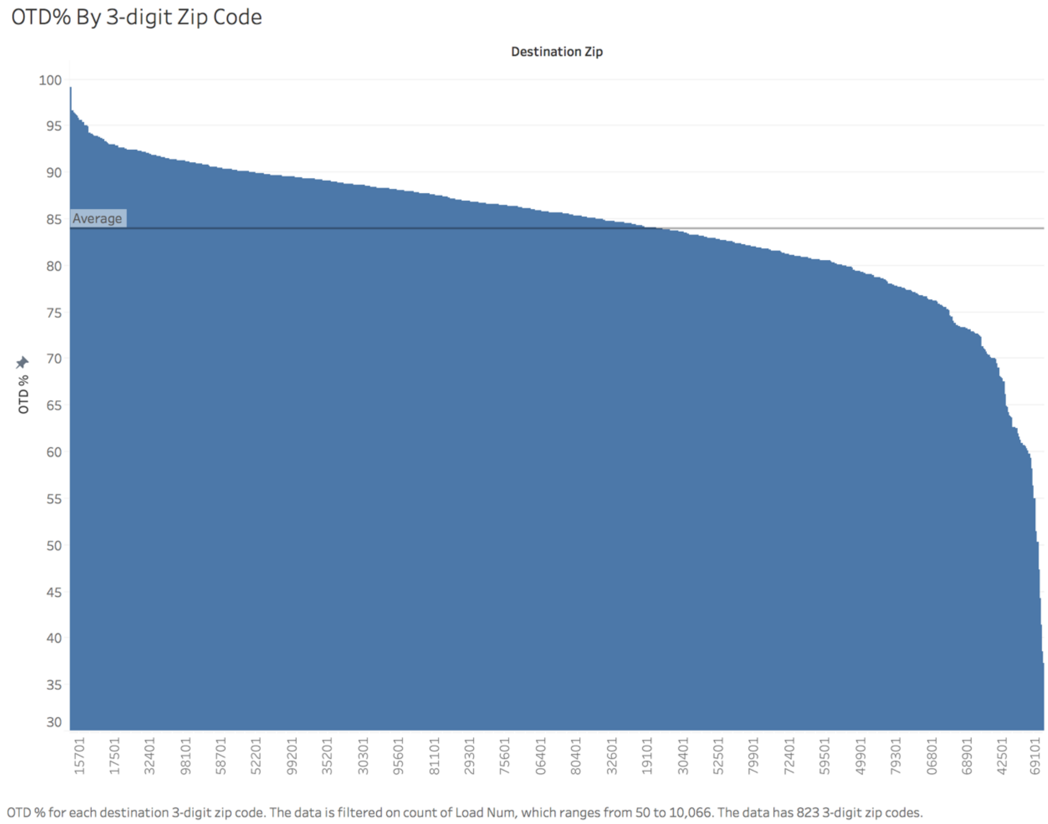



*Figure 12: On-Time Delivery Performance by 3-Digit Zip Code*

We noticed that lower performing zip codes tend to have fewer shipments, and vice versa. To validate this observation, we conducted a correlation analysis and found the correlation between count of shipment and OTD is 0.2051. We defined a new variable, named c-code zip count, which is related to geographical features and we added it back to the full and constrained dataset:

- C-code zip count: the business unit's count of loads in the destination 3-digit zip code area

Due to the large number of 3-digit zip codes, the values of the derivative variable are not presented in the article.

### 4.2.2 OTD Logistic Regression Analysis on TMC dataset

This section discusses the logistic regression models constructed to identify the significant factors. The regression models aim to quantify the correlation between on-time delivery and the remaining attributes. We followed the three parallel model structure for this section, as we did for the OTP analysis.

Due to the potentially high collinearity among the variables, a correlation analysis on the constrained dataset was conducted. It shows rate and fuel surcharge are highly related to weight and number of pallets, mile is related to published transit days, pallet position is related to number of pallets. We removed rate, miles, fuel, and pallet position for the purpose of reducing collinearity in the model.

**Correlations**

| | Rate | Miles | SMC_Transit_Days | Reference_Weight | Fuel | ActualPallets | Volume | OrdPalletPositions | Dest_dist |
|---|---|---|---|---|---|---|---|---|---|
| Rate | 1.0000 | 0.3472 | 0.2844 | 0.6789 | 0.8833 | 0.6648 | 0.3673 | 0.4906 | -0.0245 |
| Miles | 0.3472 | 1.0000 | 0.8021 | -0.0178 | 0.3101 | 0.0756 | 0.1510 | 0.0523 | -0.0397 |
| SMC_Transit_Days | 0.2844 | 0.8021 | 1.0000 | -0.0238 | 0.2325 | 0.0485 | 0.0696 | 0.0358 | 0.0885 |
| Reference_Weight | 0.6789 | -0.0178 | -0.0238 | 1.0000 | 0.5778 | 0.6870 | 0.2889 | 0.5147 | -0.0102 |
| Fuel | 0.8833 | 0.3101 | 0.2325 | 0.5778 | 1.0000 | 0.6029 | 0.4175 | 0.4333 | -0.0121 |
| ActualPallets | 0.6648 | 0.0756 | 0.0485 | 0.6870 | 0.6029 | 1.0000 | 0.3031 | 0.6750 | -0.0265 |
| Volume | 0.3673 | 0.1510 | 0.0696 | 0.2889 | 0.4175 | 0.3031 | 1.0000 | 0.2299 | 0.0041 |
| OrdPalletPositions | 0.4906 | 0.0523 | 0.0358 | 0.5147 | 0.4333 | 0.6750 | 0.2299 | 1.0000 | -0.0216 |
| Dest_dist | -0.0245 | -0.0397 | 0.0885 | -0.0102 | -0.0121 | -0.0265 | 0.0041 | -0.0216 | 1.0000 |

*Figure 13: On-Time Delivery Correlation Matrix*

The normal and constrained variables are listed in below Table 6. Normal variables have full values in the dataset, while constrained variables have varying numbers of missing values. This mirrors the structure of the OTP study. OTP here is an explanatory variable for OTD because we assumed a shipper's pick up performance may impact its delivery performance. Further, weight is further divided into high weight (weight ≥ 1000 pounds) and low weight (weight < 1000 pounds). The weight segmentation is different from that of on-time pickup analysis and this is because weight presents different patterns in OTD.

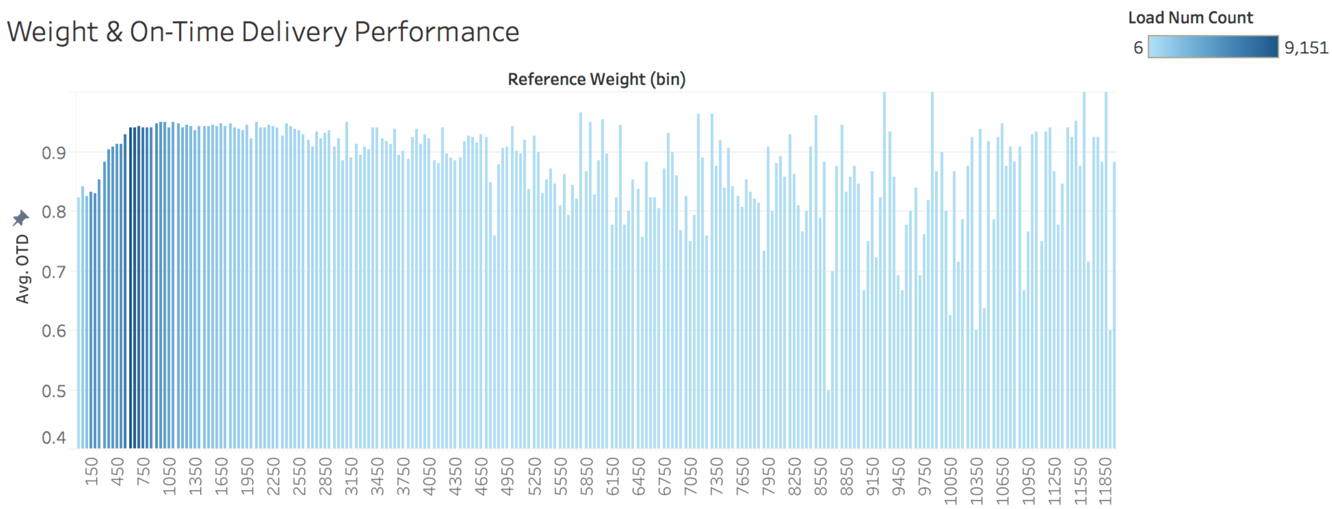



*Figure 14: Histogram of Weight & On-Time Delivery Performance*

*Table 6: On-Time Delivery Modeling Full and Constrained Variables*

| Normal Variable | Constrained Variable |
|---|---|
| SMC Transit Days | Number of Pallets |
| Weight | Volume |
| OTP | Delivery Distance |
| | C-Code Zip Count |

The result for the regression models are listed in below Table 7. For M3 (all variables on constrained dataset), a preliminary backward stepwise regression removed number of pallets, cube volume and delivery distance, with detailed result attached in appendix. Although all the models present a relatively low R^2, the p-value for certain variables are also very low, validating the significance these variables have on on-time delivery. That being said, we should not use this logistic model to make prediction, but just to understand the significant factors. Also, consistency of the coefficient is observed across all the models, meaning the models are effective.

*Table 7: On-Time Delivery Modeling Results*

| | M1 R^2: 9.77% | | M2 R^2: 9.84% | | M3 R^2: 10.07% | |
|---|---|---|---|---|---|---|
| **Term** | **Coefficient** | **P-Value** | **Coefficient** | **P-Value** | **Coefficient** | **P-Value** |
| Intercept | 1.58 | <0.0001 | 1.81 | <0.0001 | 1.71 | <0.0001 |
| SMC Transit Days (X4) | -0.3886 | <0.0001 | -0.3414 | <0.0001 | -0.3534 | <0.0001 |
| High Weight (X8d) | 0.00011 | <0.0001 | 0.0001 | <0.0001 | 0.0001 | <0.0001 |
| Low Weight (X8e) | 0.00078 | <0.0001 | 0.00025 | <0.0001 | 0.00021 | <0.0001 |
| OTP [1] (X2) | 0.8953 | <0.0001 | 1.3447 | <0.0001 | 1.3263 | <0.0001 |
| C-Code Zip Count (X12) | N/A | N/A | N/A | N/A | 0.00027 | <0.0001 |

Logistic regression equation for the M3 is:

$$P = \frac{e^{1.71-0.3534x_4+\ 0.0001x_{8d}+0.00021x_{8e}+1.3263x_2+0.00027x_{12}}}{1+\ e^{1.71-0.3534x_4+\ 0.0001x_{8d}+0.00021x_{8e}+1.3263x_2+0.00027x_{12}}}$$

High and low weight both have positive coefficient towards on-time delivery and they are similar in magnitude. This means the distinction of high and low weight is not necessary in the model. Therefore, published transit days, weight, OTP, and C-Code zip count are significant. Next, we move forward to understand how different performing shipping business units vary on these variables.

## 4.3 Leader Attributes for On-Time Performance

This section discusses how leading shipping business units are different from lagging ones on the significant variables identified. We chose to segment them based on OTD because we believe this is most valued by shippers. The case where pickup is not on-time but delivery is on-time is more acceptable than the opposite by most shippers.

Leader, middle, and laggard groups are defined at the business unit level. That is, different business units in the same company may belong to different groups. To include more data, this aggregation was done from the dataset where missing values for only the significant variables were removed. After aggregation, we filtered out those business units with fewer than 50 loads and it eventually consists of 76 business units.

After discussing with the teams from CHR and TMC, who collectively have more than 90 years of freight experience, we set forth below criteria to separate leader, middle, and laggard shipping business unit groups:

- *Leader: average OTD% ≥ 90%*
- *Middle: 80% ≤ average OTD% < 90%*
- *Laggard: average OTD% < 80%*

Table 8 summarizes the result of the segmentation and how each group performs differently on each measure. C-code zip count was replaced by the count of shipment of the business unit.

*Table 8: Leader, Middle, Laggard Attributes Summary*

| OTD Measure (%) | | | | | | |
|---|---|---|---|---|---|---|
| | # of Business Units | Mean | Min | Median | Max | Standard Deviation |
| Leader | 31 | 95% | 90% | 94% | 100% | 3% |
| Middle | 27 | 84% | 80% | 83% | 89% | 3% |
| Laggard | 18 | 59% | 27% | 59% | 78% | 13% |

| OTP Measure (%) | | | | | | |
|---|---|---|---|---|---|---|
| | # of Business Units | Mean | Min | Median | Max | Standard Deviation |
| Leader | 31 | 97% | 81% | 100% | 100% | 3.70% |
| Middle | 27 | 90% | 63% | 95% | 100% | 10% |
| Laggard | 18 | 85% | 42% | 92% | 100% | 16% |

| SMC Transit Days Measure (days) | | | | | | |
|---|---|---|---|---|---|---|
| | # of Business Units | Mean | Min | Median | Max | Standard Deviation |
| Leader | 31 | 1.71 | 1.03 | 1.75 | 2.4 | 0.37 |
| Middle | 27 | 1.93 | 1.4 | 1.79 | 3.37 | 0.44 |
| Laggard | 18 | 2.36 | 1.3 | 2.11 | 7.99 | 1.44 |

| Count of Shipment Measure (counts) | | | | | | |
|---|---|---|---|---|---|---|
| | # of Business Units | Mean | Min | Median | Max | Standard Deviation |
| Leader | 31 | 17011 | 63 | 704 | 260957 | 51562 |
| Middle | 27 | 11083 | 67 | 3071 | 74094 | 17042 |
| Laggard | 18 | 6826 | 97 | 2719 | 38727 | 11051 |

| Weight Measure (pounds) | | | | | | |
|---|---|---|---|---|---|---|
| | # of Business Units | Mean | Min | Median | Max | Standard Deviation |
| Leader | 31 | 2098 | 349 | 1552 | 6551 | 1625 |
| Middle | 27 | 2143 | 278 | 1718 | 5586 | 1665 |
| Laggard | 18 | 1839 | 185 | 1638 | 6720 | 1483 |

In addition to leading delivery performance, leaders also have the highest pickup performance (97%). Further, leaders not only have the shortest published transit days, but they also have much lower variation in this measure. The fact that the mean and the median for count of shipment are different shows that certain shippers with low shipment volume are classified into the leader group together with their larger shipment counterparts. It means small and large shippers can achieve high OTD performance. Weight shows inconsistent results over different groups. It indicates that weight may not be a good measure to segment leaders from laggards.

# 5. Results

This chapter builds upon the outcomes of the analysis and discusses the findings quantitatively and qualitatively. It is composed of two sections, one covering on-time pickup performance and the second covering on-time delivery performance.

## 5.1 On-Time Pickup Performance

We found that weight, actual pallets, distance from origin terminal, and published transit days are all correlated to on-time pickup performance. Since LTL pickups are performed via local routes making multiple stops, available capacity for both weight and number of pallets in a given truck can become an issue. If inaccurate weight or dimensional data is shared with the carrier, they may assume that all shipments can be picked up in a single route. However, if the carrier arrives and a shipment is heavier or larger than expected it may have to be rejected until another truck can come, or it may take up additional space causing issues with later pickups. This is likely why performance is so varied for shipments greater than 5,000 pounds. Figure 15 shows the negative correlation between number of pallets and on-time pickup performance. For the most part there is a steady decline in performance, but it’s also seen that the majority of shipments have only one pallet and then there is a long tail of shipments with greater than three pallets.

Distance from origin terminal has a positive correlation, however, performance is pretty stable at all distances as seen in Figure 16. When a pickup driver performs their pickup route, they typically begin with the furthest shipments and work back towards the terminal. It is possible then that closer shipments are more likely to be bumped due to lack of space in the trailer. Despite this, being closer to the terminal means that a shipper has a higher chance that a second truck could come pick up the shipment(s) on the requested day.

The final correlated variable is published transit days. While we do not want to ignore the statistical significance, it is likely that this is heavily influenced by the fact that over 40% of the loads have published transit days of one.

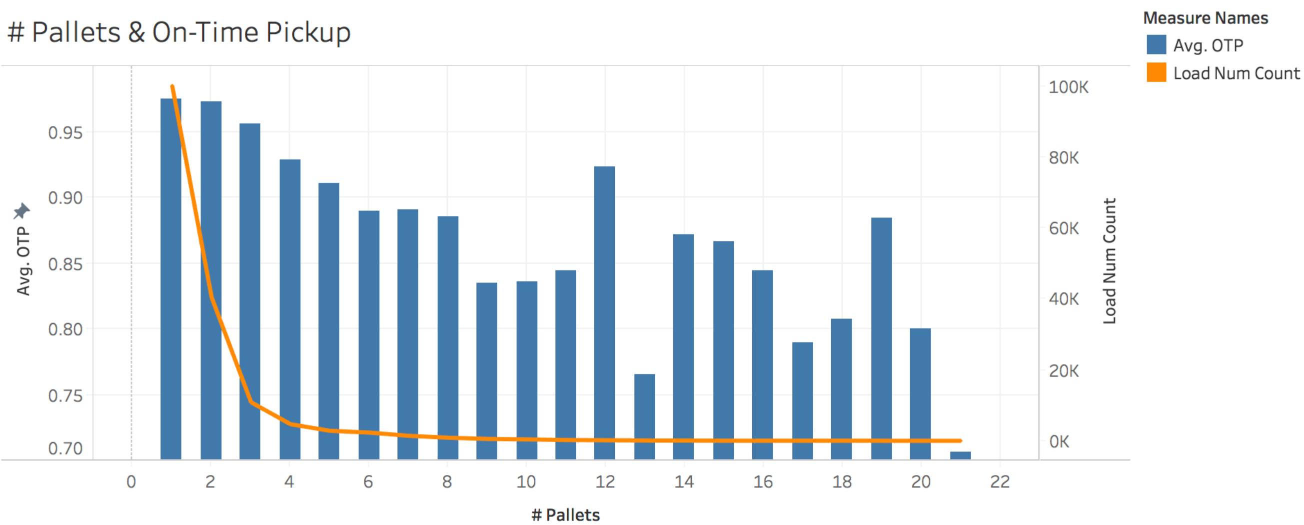



*Figure 15: Number of Pallets and On-Time Pickup Performance*

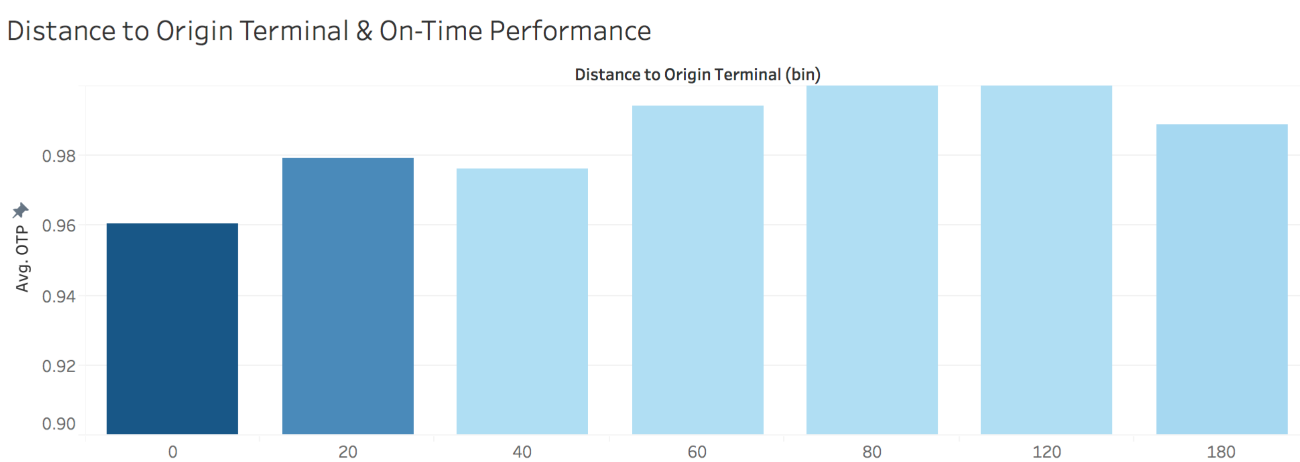



*Figure 16: Distance to Origin Terminal & On-Time Pickup Performance*

## 5.2 On-Time Delivery Performance

For OTD there are four significant variables identified from the TMC dataset: on-time pickup, published transit days, weight, and the total counts of shipments sent by the business unit to a particular 3-digit zip code.

The leader attribute on previous chapter depicts an ideal leader of high on-time delivery performance. It is one who has high on-time pickup performance (driven by its own set of attributes), is located closer to its customers (lower published transit days) and ships more shipments to high volume regions.

From the shipper's perspective, high on-time pickup performance is a combination of different factors discussed previously. A high pickup performance likely indicates better shipment management (for example, well organized outbound dock) and better shipper-carrier relationship (for example, a shipper marked as preferred shipper by carriers). Enhanced management efforts and better shipper-carrier communication also benefits the delivery performance of LTL freight.

It makes intuitive sense that shipments to higher volume regions with shorter published transit days are correlated with higher on-time delivery performance. The larger counts of shipments to a certain area, the more opportunities there are for continuous improvement. The learning opportunity increases delivery performance. Shorter published transit days mean not only the reduced number of terminals to go through, which eliminates the handling and wait time, but the reduced possibility of getting delayed due to the many other risk factors when the goods are in the carrier's hands. We also notice shipments of 6-8 published transit days seem to show an upward OTD trend. However, we do need to highlight they represent an extremely small portion of the total shipments studied (<1,000 shipments or 0.3% of the dataset).

Our research also found that although weight is generally positively related to OTD, there is a lot of variation in performance at higher weight levels. This is similar to what was seen from the perspective of pickup performance and indicates weight is a weak influencer on performance at the far ends of the weight range. Due to the ease of use of pallet jacks and forklifts, and the popularity of palletization, it makes sense that the carrier can handle most shipments easily, regardless of the weight.

The effect of delivery distance (the distance from delivery terminal to delivery point) is not statistically significant for delivery performance. This may reflect the better management of delivery arrangement.

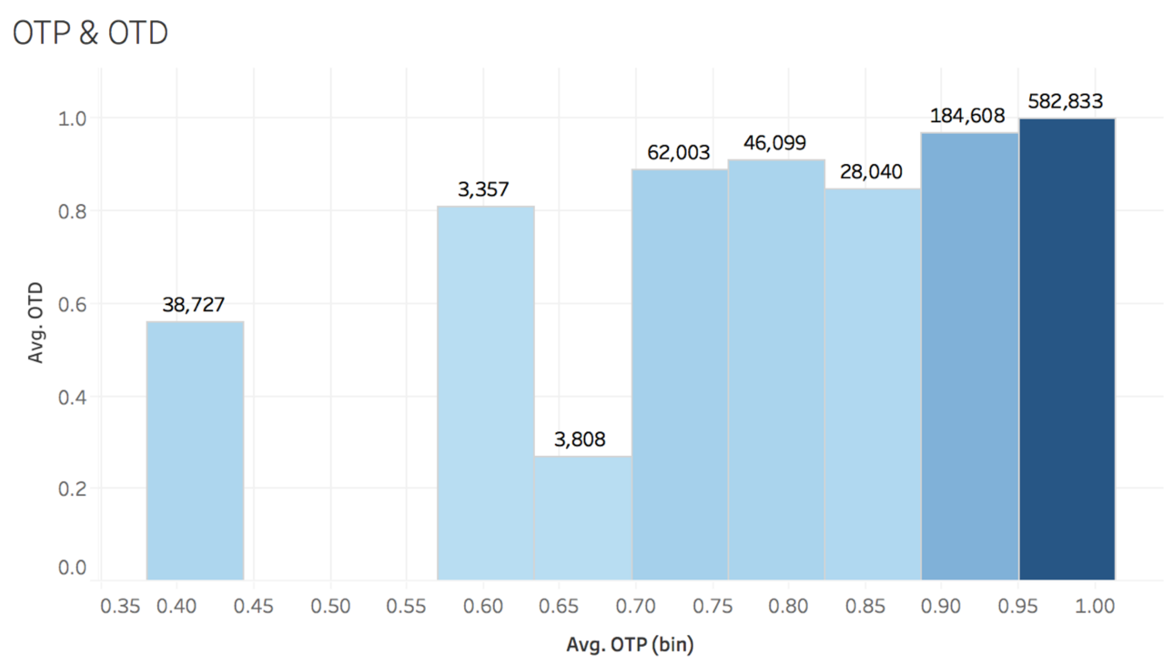



*Figure 17: On-Time Pickup & On-Time Delivery Comparison*

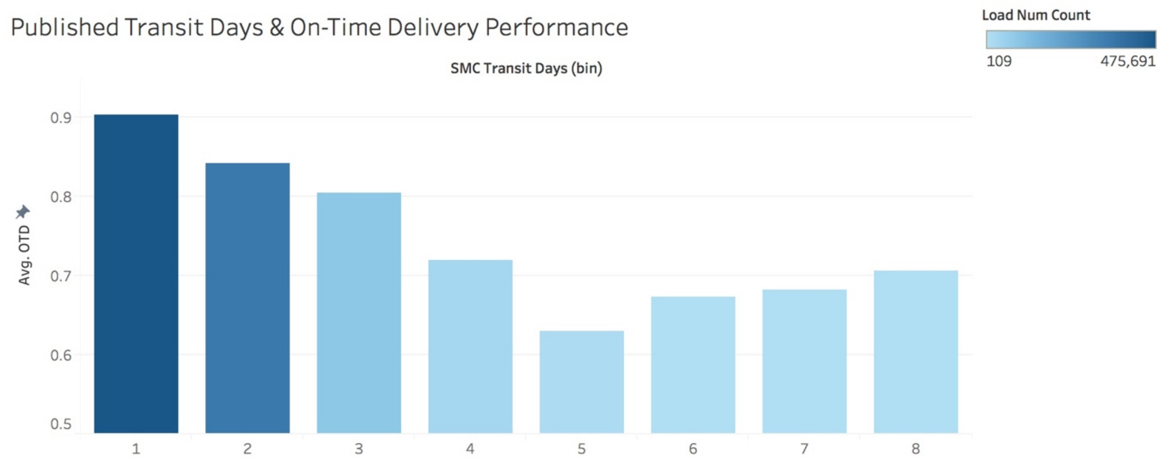



*Figure 18: On-Time Delivery Performance Compared to Published (SMC) Transit Days*

## 5.3 Perfect Shipment Performance on Outbound Dataset

Perfect shipment is defined as one that is both picked up and delivered on time. Mathematically, it is defined as a binary variable that is the product of OTP and OTD, with 1 perfect shipment and 0 not perfect shipment. As shown in the previous two sections, attributes affecting on-time performance differ between pickup and delivery. Shippers need to understand both perspectives when seeking high levels of perfect shipments. Shipments that are made up of fewer pallets going to high volume destinations will be the shipments most likely to experience perfect performance. As this is not always possible, shippers should understand what is most important to them and their customers, and where costs are driven.

## 5.4 Assessorial Charges and Special Shipment Characteristics

The dataset from TMC also included information on whether a shipment encountered an assessorial charge due to a characteristic of the shipment itself or the haul. These include hazmat, liftgate, and detention. Shipments with assessorial charges represent an extremely small percentage of the total so we chose to evaluate them independently. Table 10 highlights the different charges, the percent of shipments that encountered each charge, and the percent of shipments that were late to be picked up or delivered.

*Table 9: Assessorial Charges Breakdown*

| Assessorial | Total Counts | OTP | OTD |
|---|---|---|---|
| Hazmat | 7,299 | 95% | 67% |
| Liftgate | 5,685 | 83% | 62% |
| Detention | 57 | 88% | 93% |

Shipments containing hazardous material (hazmat) are of interest as they require special consideration when handling. Hazmat shipments must be handled with care during transport. Some carriers deal specifically with special shipping requirements such as hazmat, but often they are shipped with standard LTL carriers. When this happens, hazmat shipments can often encounter delays. This is because they often cannot be placed on the same truck as other shipments (e.g. food and beverage). This can cause hazmat shipments to be delayed at terminals awaiting a truck that can carry them towards their destination.

Liftgate shipments, like hazmat, require special handling. Typically, it is due to the origin or destination not having a loading dock. This means that these shipments must be picked up and dropped off with a trailer equipped with a liftgate. Since most trailers are not equipped with liftgates this can cause these shipments to be delayed.

The smallest assessorial group in terms of load count is detention. Detention charges are incurred in two scenarios: if the shipment is not ready when the carrier arrives for pickup or if the receiver cannot receive the shipment when it arrives. In either case the carrier is delayed and thus charges a detention fee. Since LTL networks are designed with pickup delivery routes, it is possible that carriers simply move to the next stop rather than wait. If not, it captures that shippers are very rarely unprepared for a pickup.

## 5.5 Regional and National Carrier Comparison

During this research we found some interesting performance variations between regional and national carriers. From a total network perspective, national carriers had better pickup and delivery performance. However, when we separated the shippers by Mega, Large, and Small interesting results as seen in Figure 19.

- *Small Shippers: < 25,000 total shipments*
- *Large Shippers: 25,000 – 100,000 total shipments*
- *Mega Shippers: >100,000 total shipments*

Small shippers get nearly equal performance from regional and national carriers when it comes to on-time pickup, however, regional carriers perform better for them in terms of on-time delivery. Large shippers experience they opposite, getting better performance from national carriers. This is likely due to the fact that large shippers tend to have more shipping destinations (Table 1). Mega shippers achieve the highest performance from both regional and national carriers. While we showed in the analysis that shipper size does not have a large impact on performance (i.e. small shippers can still achieve leading performance), the mega shippers all achieve leading levels of performance.

Carrier OTP Performance

| SCAC Type | Small Shippers | Large Shippers | Mega Shippers |
|---|---|---|---|
| National | 89.9% | 82.4% | 97.4% |
| Regional | 90.0% | 78.7% | 98.8% |

Carrier OTD Performance

| SCAC Type | Small Shippers | Large Shippers | Mega Shippers |
|---|---|---|---|
| National | 79.7% | 84.8% | 91.1% |
| Regional | 84.6% | 72.6% | 94.7% |

*Figure 19: Carrier (SCAC) Performance - Small vs. Large Shippers*

# 6. Discussion and Conclusion

## 6.1 Industry Recommendations

Through this research we have found many significant influencing factors on LTL shipping performance, but the significant factors influencing on-time pickup are not all the same as those for on-time delivery. Subsequently, shippers need to understand pick-up activity and delivery activity differently and take a holistic approach to on-time performance. Shippers should also evaluate the cost and ramification of not being picked up and delivered on-time respectively in their supply chain and implement different shipment tactics. On-time pickup and delivery performance have published transit days and weight in common. Shorter transit shipments tend to fare better for both pickup and delivery. When it comes to weight though, between 600 and 2000 pounds seems to be the sweet spot. Above or below this, the variance in performance is so great that it is not possible to give a solid recommendation. Shipment weight can be hard or even impossible for shippers to manipulate. The main conclusion here is that shippers should cognizant of the weights of their shipments, use this information to understand potential performance impacts, and manage expectations accordingly.

Shippers experience better on-time pickup performance when minimizing the number of pallets in a shipment. This leads back to internal and external operational practices. What is it about the shipper or their customer's production and procurement processes that drive the current volumes? Is there a more optimal process that could also improve transportation performance through different shipment sizes. It's also important to note that large LTL shipments can often be effectively shipped via truckload for similar or sometimes even lower costs. This applies to large (≥ 6,000 lbs.) LTL shipments. Those that fall in the mid-range should signal shippers to manage expectations internally and with their customers. Although this is related to on-time pickup, we’ve shown that pickup is a significant driver of on-time delivery performance.

Our research also draws insights into the additional benefit of Just-In-Time (JIT) and lean production. The JIT and lean system is essentially a pull system where the flows of materials are pulled just in time and just in the right quantity needed with the ultimate goal of eliminating wastes. A key logistics feature of JIT system is more frequent shipments of goods with smaller quantity for each shipment. Along with all other benefits, our research shows that a system like that will also have statistically higher on-time performance, which is very important to the shipper’s effective inventory and sales management. This effect can be further enhanced if the receiving warehouse has shorter published transit days from its shipping origin. It points to the strategic locating of production sites and central distribution centers. A closer to market location will not only save shipping cost but increase on time performance level.

While weight and number of pallets were the only statistically significant physical attributes of shipments and on-time pick up performance, there is a critical point to be made about capturing physical shipment data. From personal experience at a consolidation center, we learned that many shippers do not accurately measure and report their shipments’ weight, dimensions, or volume. This may lead to issues at breakbulk centers that can delay shipments and cost the shipper added fees. Going back to the importance of this, shippers should not only strive to capture as much data as possible about their shipments, but also ensure the data is accurate. Accurate data is the only way to find deficiencies and drive continuous improvement.

Furthermore, shippers should work towards integrating this data with operational data. This includes damage and loss data or production scheduling data. Additional data types will be discussed later, but often times these types of data are captured in different systems, which makes it difficult to understand correlations and impacts. There are many operational questions shippers can ask themselves. Do shippers often request spotted trailers? Do they have extremely inconsistent load quantities? Do their shipment characteristics need special blocking or bracing? Do shippers often mis-represent their shipment dimensions? Why? What is happening internally and what can be done to capture these processes so that they can be improved and transportation can be planned in a more accurate manner? Also, if more internal operational data of shippers are collected and recorded in the future, researchers can have a deeper understanding of the business logic of how certain attributes impact performance.

Finally, shippers should strive to integrate and share as much of this data as possible with TMC. TMC provides process improvement and operational expertise when it comes to shipping. Creating and fostering a collaborative relationship is critical for optimal success when it comes to transportation services and LTL specifically.

## 6.2 Further Discussion

### 6.2.1 Additional Data Points

While the data analyzed throughout this report was extensive, we believe there are important opportunities for further research. In this section we will discuss limitations of the data and analysis presented here as well as what we would recommend be investigated to complete the understanding of LTL shipping performance. The significant pieces of data that we believe should be pursued are shipment damages and shortages, invoicing accuracy, and carrier network configuration. All of these are important metrics to track when shipping LTL (Robinson 2017).

Since LTL shipments encounter more touch-points than truckload shipping, the occurrences of damage and shortage (missing pieces) can be more frequent. The difficulty with this data is that issues pertaining to these matters are typically handled by the shippers themselves rather than a transportation services provider such as TMC. This data would help us understand the correlation between in-transit damages or shortages and on-time performance. Furthermore, it can also help us to understand if carriers more often alert shippers and customers of issues mid-shipment, or if the shipment makes it to its destination before the indemnity process is initiated.

The second piece of data that would be useful for further research is on invoicing accuracy. According to Maersk CEO, Soren Skou, 12 percent of invoices in the container industry are inaccurate (Biederman 2013). We believe this significant level of inaccuracy is present in the trucking industry as well. Invoice inaccuracy can lead to high costs for shippers and their customers. With this data we can find the root cause of these errors and quantify their impact on on-time performance.

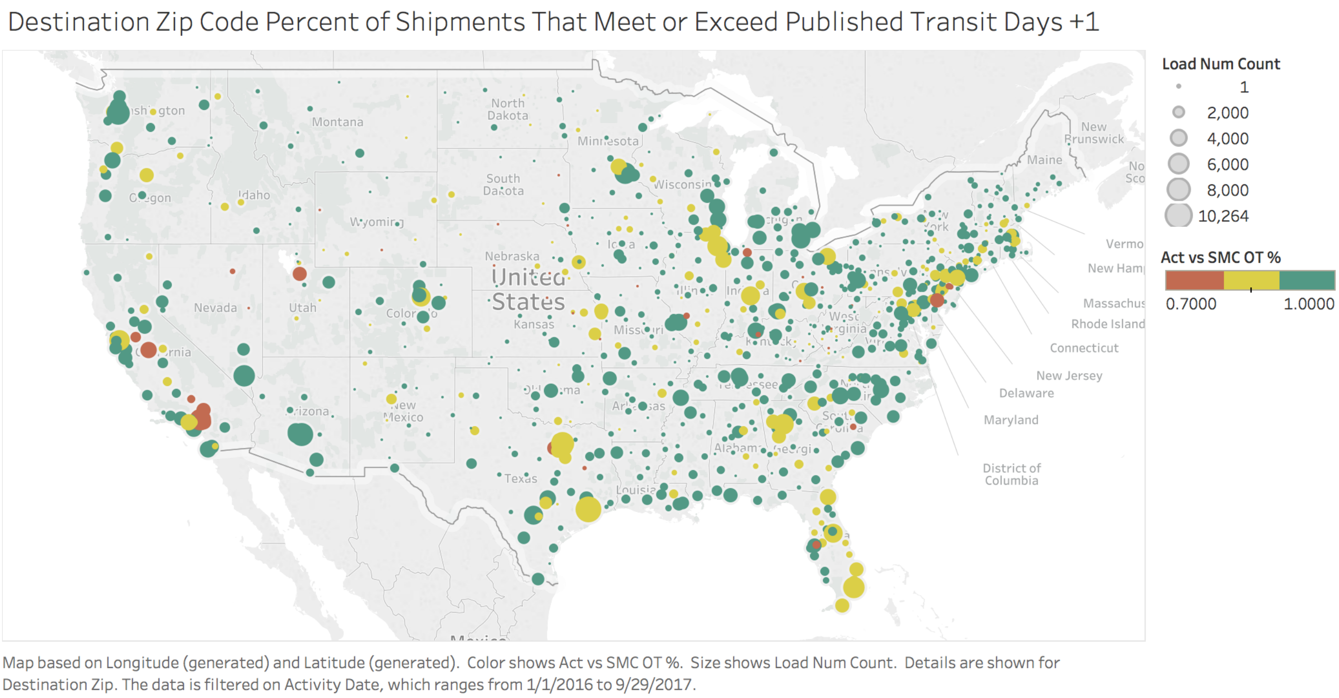
The final data element we believe is significant to future analysis is carrier network configuration. As previously mentioned in this report, we evaluated the effects of shipment mileage and published lane transit days on on-time performance. However, with carrier network information we could understand how many terminals a given shipment would encounter while in-transit. We could also evaluate where a shipment may be interlined between multiple carriers. Having knowledge of the potential number of touchpoints that a shipment will experience can be correlated to both damage and shortage, as well as on-time performance.

It is our belief that these additional data points will aid in understanding, holistically, what factors have the largest impact on LTL performance. It is also viable that these factors could be added to perfect shipment calculation to broaden it beyond simply on-time performance.

### 6.2.2 Performance to Published Transit Times & Tender Codes

In this research we defined on-time performance as actual dates to scheduled dates. Another performance metric that is used in the trucking industry is performance to published transit times. As previously mentioned, published transit times are represented by SMC transit days in our dataset. We performed some additional research to see how the actual transit days of our shipment dataset compared to the published transit days. With initial input from CHR and TMC we expected to see higher performance from this metric. We were surprised to find that shipments actually performed worse with only 71% of shipments being delivered in equal to or less than the published transit days. However, the dataset does not capture incidents that would lead to delays. In trucking these incidents are captured by tender codes.

Tender codes are attached to shipment records to indicate specific events that happened during pickup, transit, or delivery. Tender codes include reasons such as location issues (unable to locate address), customer signature requested, holidays, adverse weather, and many more. Additionally, nearly half of these codes result in the shipment being “taken out of service”. This does not mean the shipment will no longer be delivered, it means that the shipment will not be considered late if delivered after the scheduled date or published days. With this in mind we recalculated the performance figures but added one day to the published transit times to account for unforeseen delays (events). The results are shown in Figures 20 and 21. The performance figures are much more favorable with 91% of shipments being delivered in equal to or less than the published transit days. What is important for shippers to take from this is that there are dozens of reasons that a shipment may get delayed. Some of these reasons can be mitigated through communication between shipper, customer, and carrier (such as incorrect address or special handling requirements). Furthermore, if such a delay is inevitable, or even if something like adverse weather is expected, shippers who understand the impact and associated tender codes can better manage expectations of on-time performance.




**Note: OTD performance → Red < 80%, Yellow 80-90%, Green > 90%*

*Figure 20: Destination Zip Code Actual Transit Days vs. Published Transit Days +1*

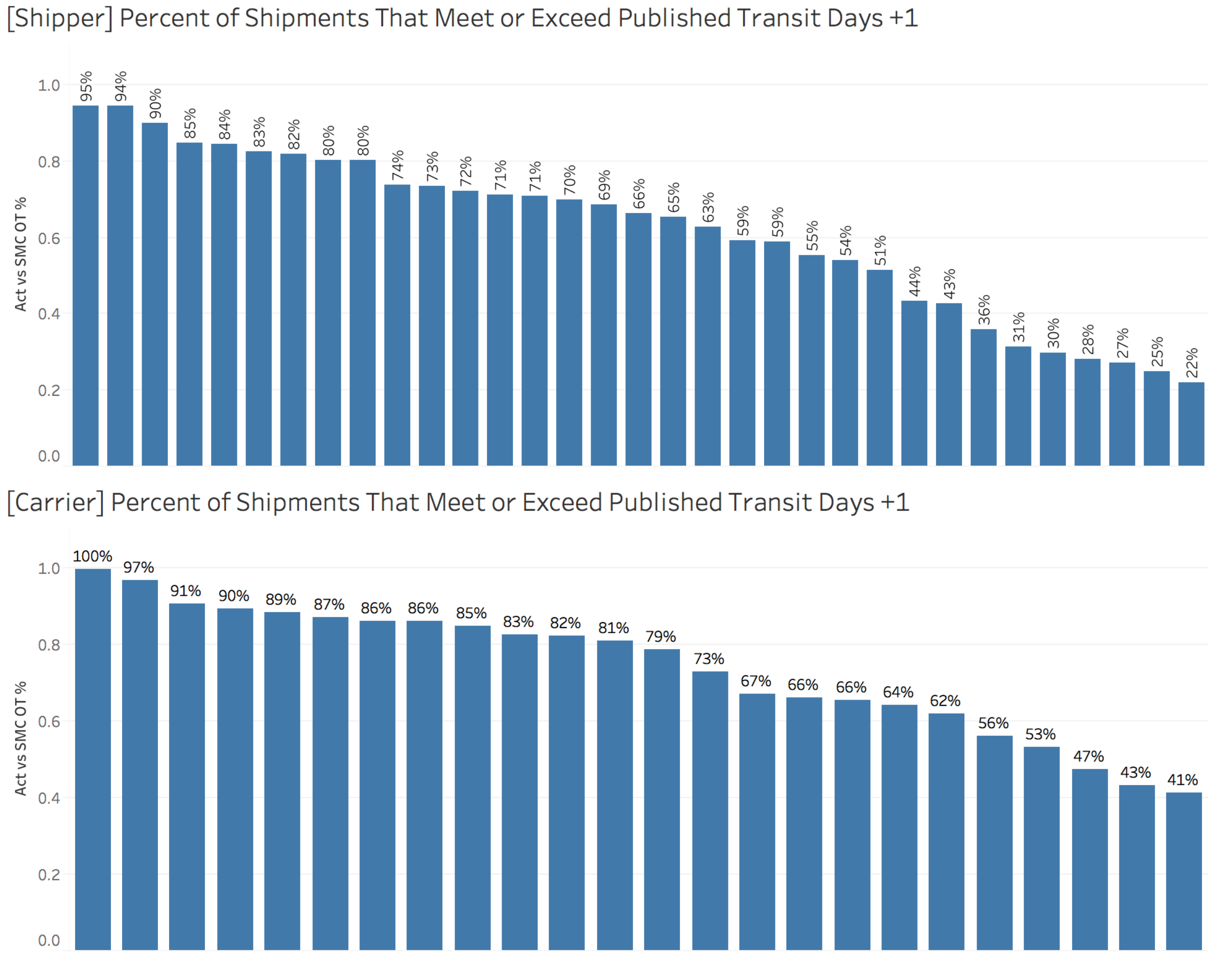



*Figure 21: Shipper & Carrier Percent of Shipments that Meet or Exceed Published Transit Days +1*

## 6.3 Conclusion

Over the course of this research, it has been affirmed that the biggest drivers of LTL on-time performance are shipment size (weight and number of pallets), distance of the shipment, and volume of the destination lane. We have shown that shipment size has a greater impact on pickup performance while distance and lane volume have a greater impact on delivery performance. Shippers must understand that there is much more variance in LTL than truckload when it comes to attributes that affect this performance. Due to this variance, shippers should seek to gather as much data as possible on each of their shipments. With this they can understand and manage the expectations of on-time performance. They must align with the needs of customers and carriers. By working with customers, they may be able optimize shipment sizes that perform better with carriers. While changing locations is an unrealistic change in most cases, shippers can choose more conservative delivery dates when shipping to low volume areas and expect that shipments to high volume areas will experience better service. Going forward shippers need to be more collaborative with their logistics providers (TMC) and freight forwarders. Without collaboration, there cannot be an environment of continuous improvement. Without continuous improvement, shippers will struggle to succeed in a world dominated by just-in-time supply.

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# Appendices

## Appendix A - Regression Results for OTD Analysis

### Model 1

**Whole Model Test**

| Model | -LogLikelihood | DF | ChiSquare | Prob>ChiSq |
|---|---|---|---|---|
| Difference | 37270.91 | 4 | 74541.82 | <.0001* |
| Full | 344097.92 | | | |
| Reduced | 381368.83 | | | |

| | |
|---|---|
| RSquare (U) | 0.0977 |
| AICc | 688206 |
| BIC | 688265 |
| Observations (or Sum Wgts) | 947221 |

**Fit Details**

| Measure | Training | Definition |
|---|---|---|
| Entropy RSquare | 0.0977 | 1-Loglike(model)/Loglike(0) |
| Generalized RSquare | 0.1368 | (1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n)) |
| Mean -Log p | 0.3633 | $\sum -\text{Log}(\rho[j])/n$ |
| RMSE | 0.3283 | $\sqrt{\sum(y[j]-\rho[j])^2/n}$ |
| Mean Abs Dev | 0.2147 | $\sum \lvert y[j]-\rho[j]\rvert/n$ |
| Misclassification Rate | 0.1391 | $\sum(\rho[j] \neq \rho\text{Max})/n$ |
| N | 947221 | n |

**Lack Of Fit**

**Parameter Estimates**

| Term | Estimate | Std Error | ChiSquare | Prob>ChiSq |
|---|---|---|---|---|
| Intercept | 1.57763739 | 0.0085183 | 34301 | <.0001* |
| SMC_Transit_Days | -0.388569 | 0.0029386 | 17484 | <.0001* |
| High Weight | 0.00010587 | 2.6377e-6 | 1611.1 | <.0001* |
| Low Weight | 0.00078381 | 1.2769e-5 | 3768.1 | <.0001* |
| OTP[1] | 0.89531104 | 0.0041121 | 47406 | <.0001* |

For log odds of 1/0

**Covariance of Estimates**

**Effect Likelihood Ratio Tests**

**Confusion Matrix**

Training

| Actual | Predicted Count | |
|---|---|---|
| OTD | 1 | 0 |
| 1 | 805299 | 10531 |
| 0 | 121262 | 10129 |

### Model 2

**Ordinal Logistic Fit for OTD**

**Effect Summary**

**Whole Model Test**

| Model | -LogLikelihood | DF | ChiSquare | Prob>ChiSq |
|---|---|---|---|---|
| Difference | 7205.672 | 4 | 14411.34 | <.0001* |
| Full | 66048.365 | | | |
| Reduced | 73254.037 | | | |

| | |
|---|---|
| RSquare (U) | 0.0984 |
| AICc | 132107 |
| BIC | 132159 |
| Observations (or Sum Wgts) | 280605 |

**Fit Details**

| Measure | Training | Definition |
|---|---|---|
| Entropy RSquare | 0.0984 | 1-Loglike(model)/Loglike(0) |
| Generalized RSquare | 0.1231 | (1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n)) |
| Mean -Log p | 0.2354 | $\sum -\text{Log}(\rho[j])/n$ |
| RMSE | 0.2477 | $\sqrt{\sum(y[j]-\rho[j])^2/n}$ |
| Mean Abs Dev | 0.1223 | $\sum \lvert y[j]-\rho[j]\rvert/n$ |
| Misclassification Rate | 0.0738 | $\sum(\rho[j] \neq \rho\text{Max})/n$ |
| N | 280605 | n |

**Lack Of Fit**

**Parameter Estimates**

| Term | Estimate | Std Error | ChiSquare | Prob>ChiSq |
|---|---|---|---|---|
| Intercept[1] | 1.80935213 | 0.0244336 | 5483.7 | <.0001* |
| SMC_Transit_Days | -0.3413521 | 0.0098317 | 1205.5 | <.0001* |
| High Weight | 0.00010181 | 8.8321e-6 | 132.87 | <.0001* |
| Low Weight | 0.00024841 | 3.0278e-5 | 67.31 | <.0001* |
| OTP[1] | 1.34472396 | 0.0111353 | 14583 | <.0001* |

**Effect Likelihood Ratio Tests**

**Confusion Matrix**

Training

| Actual | Predicted Count | |
|---|---|---|
| OTD | 1 | 0 |
| 1 | 257778 | 2373 |
| 0 | 18347 | 2107 |

### Model 3

**Whole Model Test**

| Model | -LogLikelihood | DF | ChiSquare | Prob>ChiSq |
|---|---|---|---|---|
| Difference | 7374.694 | 5 | 14749.39 | <.0001* |
| Full | 65879.343 | | | |
| Reduced | 73254.037 | | | |

| | |
|---|---|
| RSquare (U) | 0.1007 |
| AICc | 131771 |
| BIC | 131834 |
| Observations (or Sum Wgts) | 280605 |

**Fit Details**

| Measure | Training | Definition |
|---|---|---|
| Entropy RSquare | 0.1007 | 1-Loglike(model)/Loglike(0) |
| Generalized RSquare | 0.1259 | (1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n)) |
| Mean -Log p | 0.2348 | $\sum -\text{Log}(\rho[j])/n$ |
| RMSE | 0.2481 | $\sqrt{\sum(y[j]-\rho[j])^2/n}$ |
| Mean Abs Dev | 0.1224 | $\sum \lvert y[j]-\rho[j]\rvert/n$ |
| Misclassification Rate | 0.0755 | $\sum(\rho[j] \neq \rho\text{Max})/n$ |
| N | 280605 | n |

**Lack Of Fit**

**Parameter Estimates**

| Term | Estimate | Std Error | ChiSquare | Prob>ChiSq |
|---|---|---|---|---|
| Intercept[1] | 1.7127275 | 0.0248733 | 4741.5 | <.0001* |
| SMC_Transit_Days | -0.3534062 | 0.0097704 | 1308.3 | <.0001* |
| High Weight | 0.00010303 | 8.7531e-6 | 138.54 | <.0001* |
| Low Weight | 0.00021347 | 3.0243e-5 | 49.82 | <.0001* |
| OTP[1] | 1.32630068 | 0.0111911 | 14046 | <.0001* |
| C-Code Zip Count | 0.00027025 | 1.5359e-5 | 309.59 | <.0001* |

**Effect Likelihood Ratio Tests**

**Confusion Matrix**

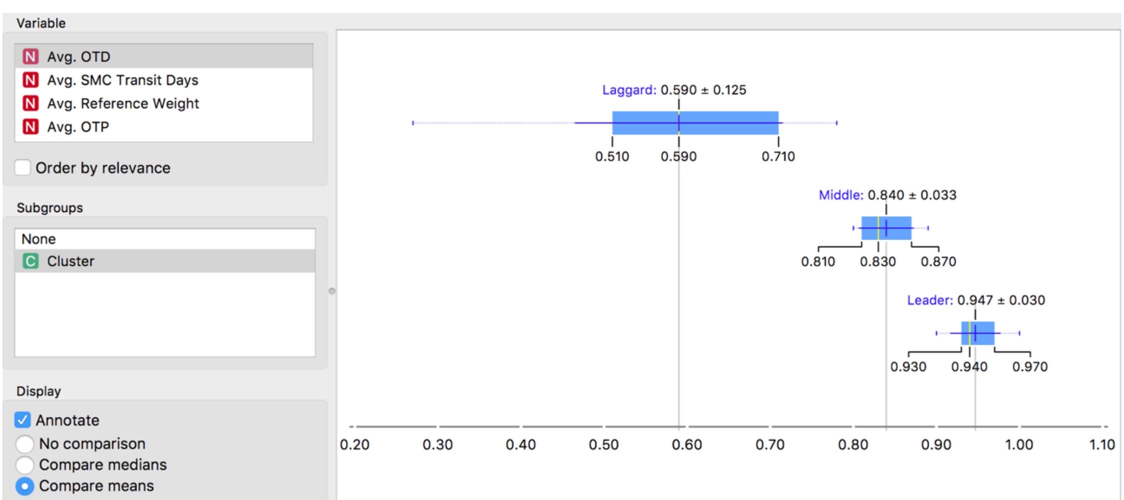
Training

| Actual | Predicted Count | |
|---|---|---|
| OTD | 1 | 0 |
| 1 | 257795 | 2356 |
| 0 | 18837 | 1617 |

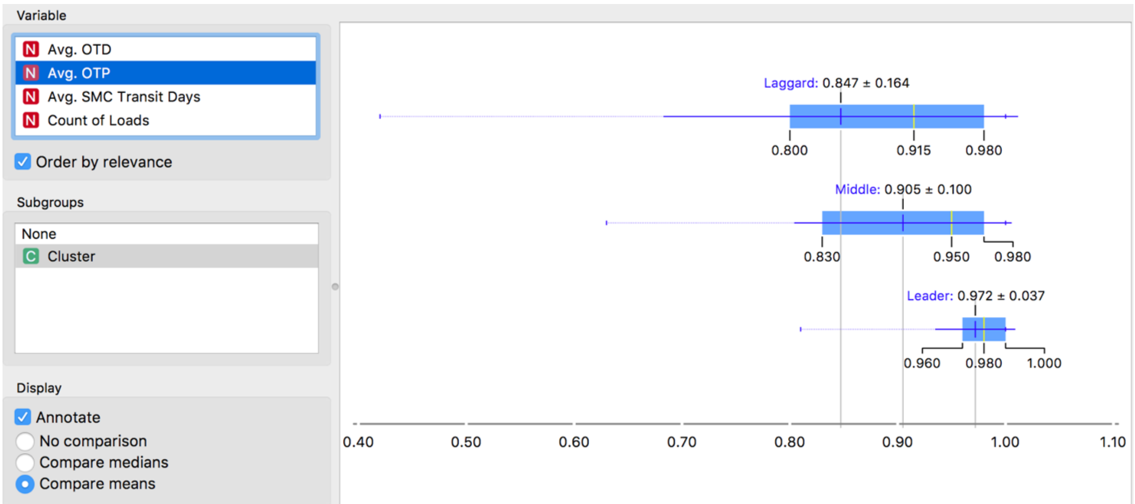
The 3 results show consistency of the sign of the coefficients across 3 models.

## Appendix B - Box Plots for Significant Attributes of Leaders, Middle and Laggard Groups

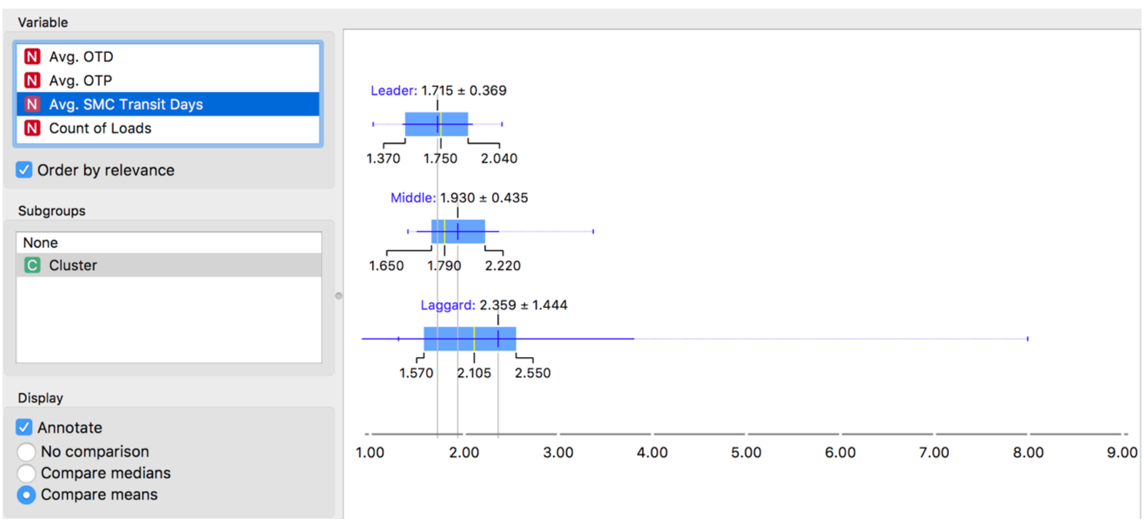
OTD Ratio



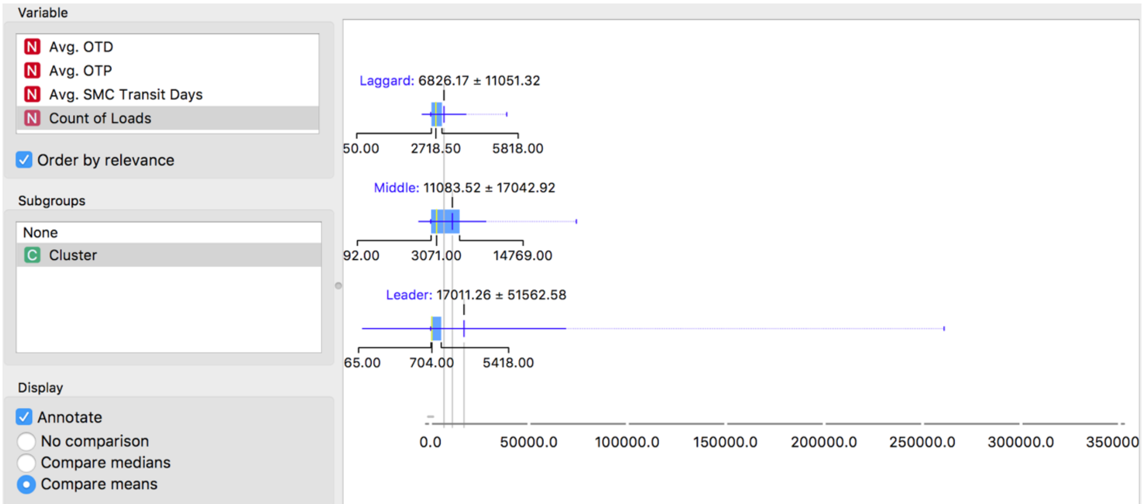
OTP Ratio



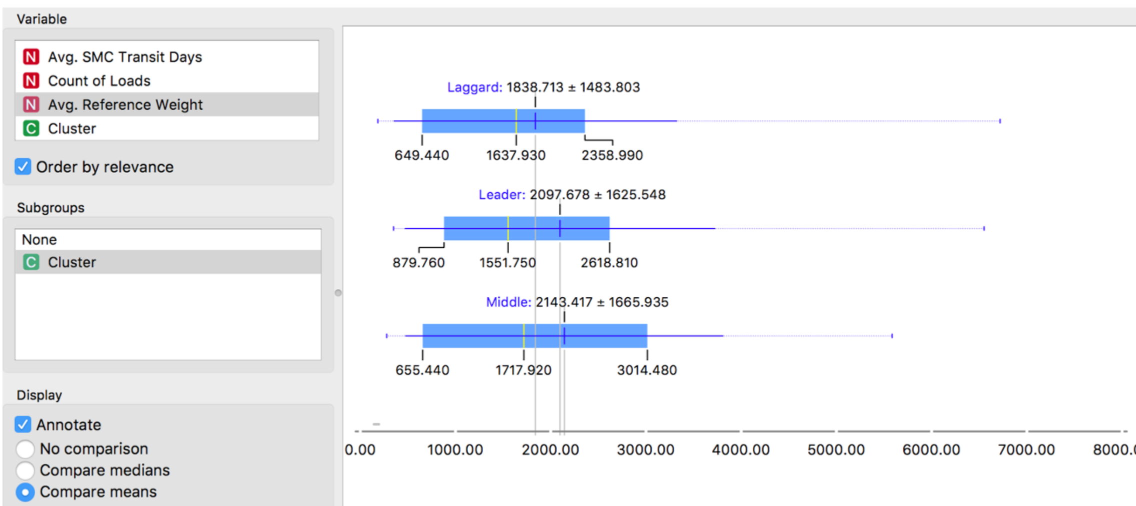

Published (SMC) Transit Days



Counts of Loads




Shipment Weight




These box plots show in detail how different groups perform differently in the segmentation measures.