Goldilocks and the Three Dispatchers: Quantifying the Impact of Dispatcher Management on Truck Driver Performance

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ABSTRACT

Though critical to the US economy and moving the majority of US freight, the American trucking industry faces three compounding challenges: driver shortage, low driver utilization, and high driver turnover. Previous studies have found that, though scarce, drivers are underutilized and prone to frequent employment changes, further exacerbating the shortage problem. To identify the root causes and offer potential solutions, this study investigates the impact of carrier dispatchers on truck driver performance. This performance was measured by three key metrics: Hours of Service utilization, average miles driven per day efficiency, and employee retention. ELD and TMS data from a midsized carrier was run through regression and clustering machine learning algorithms to evaluate the features impacting these metrics. It was found that dispatchers indeed impact driver performance and have at least three managerial levers that can be used to improve fleet performance, including the weekday a driver works, the equality of distribution of freight plans, and the size of the team a dispatcher manages. With these levers, freight carriers can themselves mitigate the impact from the challenges facing the American freight industry today.

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Danielle Procter

To Jesus, my cornerstone. To my wonderful wife Acsa, for all the love and immeasurable support, I love you! To my daughters, Rebecah and Isabella, you fill my days with joy. To my parents, my greatest masters. To Talita and family, my sister of adventures since childhood. To my advisor, Dr. David Correll, my project partner, Danielle Procter, my class colleagues and all the SCM / CTL / MIT, what a privilege to be part of this unique team. To Fonte da Vida church, my family of faith.

"The fear of the LORD is the beginning of wisdom..." (Prov.9:10)

Paulo Sousa Jr.

Table of Contents

List of Figures

List of Tables

1. Introduction

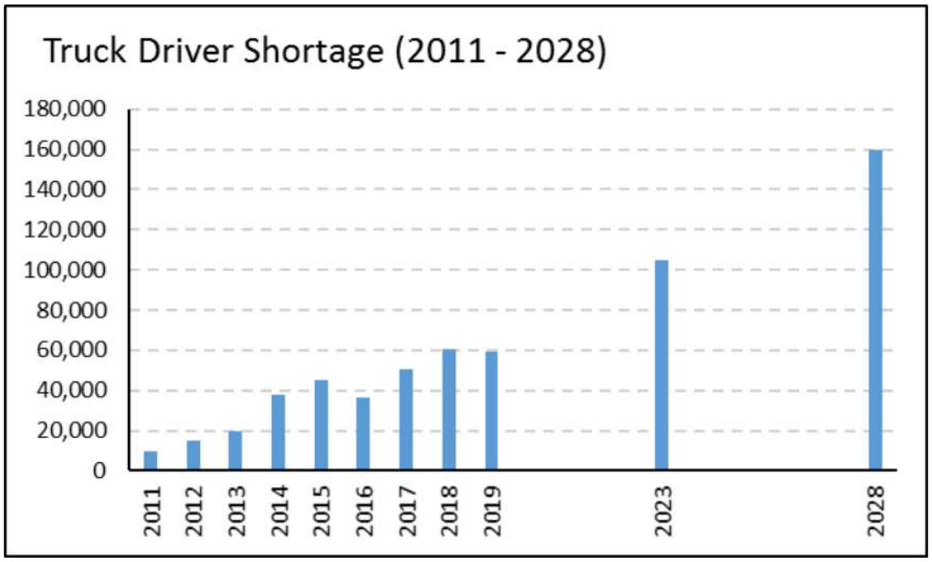
1.1. *Motivation & Relevance: The American Trucking Industry – Driver Shortage, High Turnover, and Low Utilization*

In the United States, overland trucking is a nearly $800 billion industry and accounts for 72.5% of freight movements (American Trucking Associations [ATA], 2020). To support this shipment volume, there are approximately 3.5 million truck drivers, including 2 million registered heavy and tractor-trailer drivers (U.S. Bureau of Labor Statistics, 2020) whose combined wages make up 33-43% of freight trucking costs annually (American Transportation Research Institute [ATRI], 2019)(ATA, 2020). Despite its importance, the truck driving profession is characterized by high turnover, as individual drivers move between carriers (94% turnover rate in 2017 (ATA, 2019)) or transition into other industries (22% turnover rate in 2017(Burks & Monaco, 2019)).

Additionally, truck drivers are simultaneously under-utilized and scarce (D. Correll, 2019). Many studies show an increasing truck driver shortage expected to reach 160,000 drivers short within the next eight years (ATA, 2019). Figure 1.1 shows the historical and projected growth of the US driver shortage. Because of this shortage, even incremental gains in efficiency and therefore driver utilization could have a significant impact on the industry as a whole and a marked improvement in the lives of individual truck drivers.

Figure 1.1

Truck Driver Shortage Analysis 2019



Note. Adapted from ATA, July 2019.

This carrier has provided six months of data on truck driver movements, including stop times and locations, available hour usage, and employment histories and terminations. While the data available is limited to a single transport company and to long distance "over the road" (OTR) drivers, these issues are understood to universally impact all aspects of the trucking industry and opportunities for improvement proposed in our study could likely be applied industry wide.

1.2. *Problem Statement & Key Research Question*

This capstone project leverages this driver movement data to explain the imbalance between driver availability and hour usage, and to offer managerial opportunities to improve driver performance. Specifically, it will explain the chronically low utilization and high turnover among American over the road truck drivers and suggest actionable insights to improve. While past work at MIT and beyond has sought to explain and resolve this delta, additional opportunities for research remain.

1.3. *Introduction to Freight Carrier Operations*

Freight carriers operate functionally as service providers, collecting requests for freight movements from customers and organizing their employees to complete these requests. Resources (drivers, trucks, etc.) are allocated as optimally or efficiently as possible while still meeting customer needs. The internal carrier hierarchy ensures both priorities - efficient operations and a high level of customer service - are maintained. Understanding the impact of these internal teams on the efficiency and efficacy of OTR truckers will help to explain their impact on the success metrics of these drivers.

The process for receiving and assigning OTR freight orders flows through the carrier organization. While the particulars of the process described here are specific to the partnering carrier, most of the process is generalizable to US based midsized and large freight carriers. Customers operate on a procurement system where freight shipments are offered to the spot market for carriers to bid on or are pre-planned through freight contracts. Once a carrier accepts an order, planners for that carrier assign the most appropriate driver based on the drivers' needs and the parameters established by the customer. Specifically, planners look to maintain driver efficiency by assigning loads that minimize driver wait time, minimize deadheading (miles driven without transporting goods), and maximize utilization of available HOS.

Once a freight order has been assigned by the planners, dispatchers are tasked to convey the orders and any additional relevant information to the drivers. Dispatchers work as a driver's direct supervisor and direct point of contact with the carrier. Specifically, dispatchers relay all necessary information and updates, receive and catalog driver concerns, and act as the drivers' representative within the carrier. A good dispatcher is described by the partnering carrier as capable of encouraging drivers to achieve more miles driven, balancing driver needs with the needs of the company, and allowing drivers to feel supported by the carrier firm overall. A successful dispatcher should have a group of drivers (typically 30-60 drivers per dispatcher) who achieve a competitive volume of loaded miles driven and a higher than average rate of retention (NPTC, 2019).

1.4. *Electronic Logging Device and Hours of Service Regulations*

Federal Motor Carrier Safety Administration (FMCSA) hours of service (HOS) is the legal instrument that determines the maximum amount of time drivers can be on duty. It specifies driving time limits and the minimum duration of rest periods; aiming to ensure that drivers stay awake and alert while driving. Table 1 summarizes HOS regulations for property-carrying truck drivers under these laws.

Table 1
Hours-Of-Service Regulations for Property-Carrying Drivers

11-Hour Driving Limit	May drive a maximum of 11 hours after 10 consecutive hours off duty.
14-Hour Limit	May not drive beyond the 14th consecutive hour after coming on duty, following 10 consecutive hours off duty.
30-Minute Driving Break	Drivers must take a 30-minute break when they have driven for a period of 8 cumulative hours without at least a 30-minute interruption. The break may be satisfied by any non-driving period of 30 consecutive minutes.
60/70-Hour Limit	May not drive after 60/70 hours on duty in 7/8 consecutive days. A driver may restart a 7/8 consecutive day period after taking at least 34 consecutive hours off duty.
Adverse Driving Conditions	Drivers are allowed to extend the 11-hour maximum driving limit and 14-hour driving window by up to 2 hours when adverse driving conditions are encountered.
Sleeper Berth Provision	Drivers may split their required 10-hour off-duty period, as long as one off-duty period (whether in or out of the sleeper berth) is at least 2 hours long and the other involves at least 7 consecutive hours spent in the sleeper berth. All sleeper berth pairings must add up to at least 10 hours. When used together, neither time period counts against the maximum 14- hour driving window.

Note. Adapted from Federal Motor Carrier Safety Administration [FMCSA], 2020.

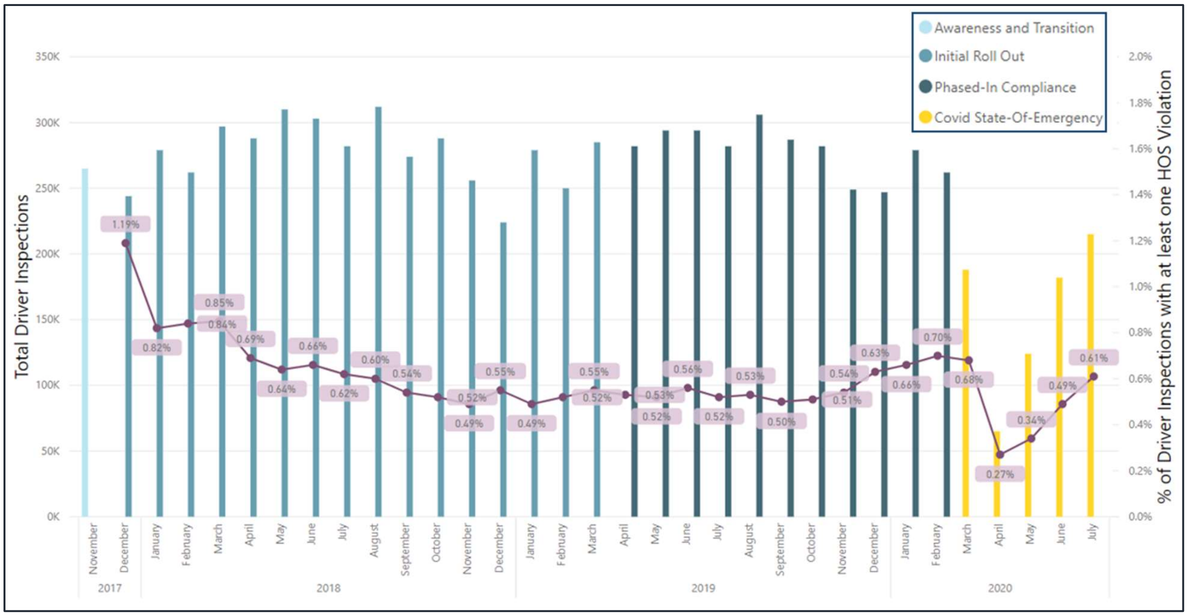
In December 2019, electronic logging device (ELD) regulation reached its full compliance phase in the United States. ELDs synchronize with a vehicle engine to automatically record driving time, providing more accurate HOS recording than was previously available with paper logbooks. Since the full compliance deadline, all drivers and carriers subject to the rule must use self-certified and FMCSA registered ELDs to record both on and off-duty time in records of duty status (RODS).

The ELD mandate has its origin in 2012, with the passage of the Moving Ahead for Progress in 21st Century Act (MAP-21) through the United States Congress. In addition to other policies, this bill authorized the FMCSA to begin drafting regulations mandating the use of electronic logging devices. The final version of the rule was published in December 2015 by FMCSA. Its implementation plan had three stages: i) Awareness and Transition (December 2015 to December 2017); ii) Phase-In Compliance (December 2017 to December 2019); and iii) Full Compliance (December 2019 onward).

The ELD mandate was conceived with two main purposes, according to its Executive Summary (FMCSA, 2015): to improve commercial motor vehicle (CMV) safety by improving compliance with HOS rules and to reduce the overall paperwork burden for both motor carriers and drivers. Figure 1.2 shows that indeed HOS compliance has improved with the implementation of the ELD mandate. The percentage of driver inspections with at least one HOS violation (weekly or daily limits) decreased by almost 50%, from the end of the Awareness and Transition stage (December 2017) to the start of Full Compliance stage (December 2019).

Figure 1.2

Hours of Service Compliance with ELD Rollout



Note. Adapted from FMCSA, 2020.

Due to the COVID-19 pandemic, the United States Federal Government declared a national emergency in March 2020. In this context, FMCSA issued an emergency declaration in the same month providing HOS relief to truck drivers transporting emergency supplies. The declaration was subsequently updated in March and April 2020 to include fuel haulers and to provide additional guidance on driver credentials and "mixed loads" (American Transportation Research Institute & Owner-Operator Independent Driver Association Foundation [ATRI & OOIDA], 2020). This HOS relaxation may explain the drastic decrease in both the inspection and violation curves in March 2020, seen in Figure 1.2.

1.5. *Methodology: Use of ELD for Understanding Truck Driver Utilization and Turnover*

ELDs facilitate the tracking, management, and sharing of trucking operational data. HOS compliance represents only the minimum functionality requirements of an FMCSA-compliant ELD. Beyond this baseline, most ELD models collect additional data including driver tasks, fuel use, state crossings, over-speed data, geographic position, odometer readings, and engine performance (D. H. Correll, 2018). This data can then be shared with carrier dispatchers and management teams.

Zhang and Buttgenbach (2020) illustrates the value of using electronic logging data to identify the underlying factors on time spent at stops and found that management of this dwell time can allow for better utilization of driving hours. Through the use of ELD data, they identified three significant factors in improving driver utilization: i) the time of day the driver arrives at a shipper location; ii) the impact from a specific location; and iii) the frequency that the carrier visits a specific shipper. Their research suggests that further analysis on electronic logging device data could result in efficiency gain.

For this research project, we focus on the relationship between driver and employer, specifically the relationship between driver and dispatcher. In traditional carrier trucking, dispatchers act as a driver's direct manager and are responsible for assigning loads and conveying all necessary information. While several studies extol the value of perceived institutional support for driver retention (Large et al., 2014)(Keller & Ozment, 1999), few recent studies have specifically investigated the impact of the driver/dispatcher relationship on this perception of support. Additionally, one of the principal findings of Zhang and Buttgenbach (2020) is that familiarity of a driver with a particular stop location can have a meaningful impact on reducing the dwell time at that location. One assumption from that study was that dispatchers would be able to share information about these stops across multiple drivers to improve efficiency overall; an indication that dispatchers may be a critical component of driver success.

In addition to the ELD data used by the Zhang and Buttgenbach (2020) study, our partnering carrier has supplied data regarding driver turnover. By using machine-learning techniques on this electronic logging device data paired with these truck driver employment histories, this research project identifies factors that contribute to driver performance in three key metrics: utilization of driving hours, efficiency in miles driven per day, and driver retention. The results from these algorithms reveal that there are inherent tradeoffs in the management of driver performance and that dispatchers must apply managerial levers appropriately. Specifically, this study identifies three different classes of dispatchers, analogous to the children's story of "Goldilocks and the Three Bears." Too rigid "Papa Bear" dispatchers see the highest productivity but lowest retention in their drivers, while the "Mama Bear" dispatchers see the opposite, long retention with low productivity. This study also shows that there is a "just right" dispatcher class who leverage management techniques to balance productivity with retention using the levers identified.

2. Literature Review

While low driver utilization and high driver turnover is a well-established problem in the US freight trucking industry, there is little consensus as to the root causes or opportunities for improvement. In the trucking industry, driver turnover rates regularly approach 100% annually, meaning that most drivers who enter a new driving role will be terminated or will leave that role by year's end (ATA, 2019). Though this turnover leads to managerial discord, it is unclear whether it contributes significantly to the driver shortage. Gallup found in 1997 that 80% of turnover in the trucking industry is due to intra-industry "churn" where drivers are leaving carriers but remaining within the trucking industry (Gallup Organization, 1997).

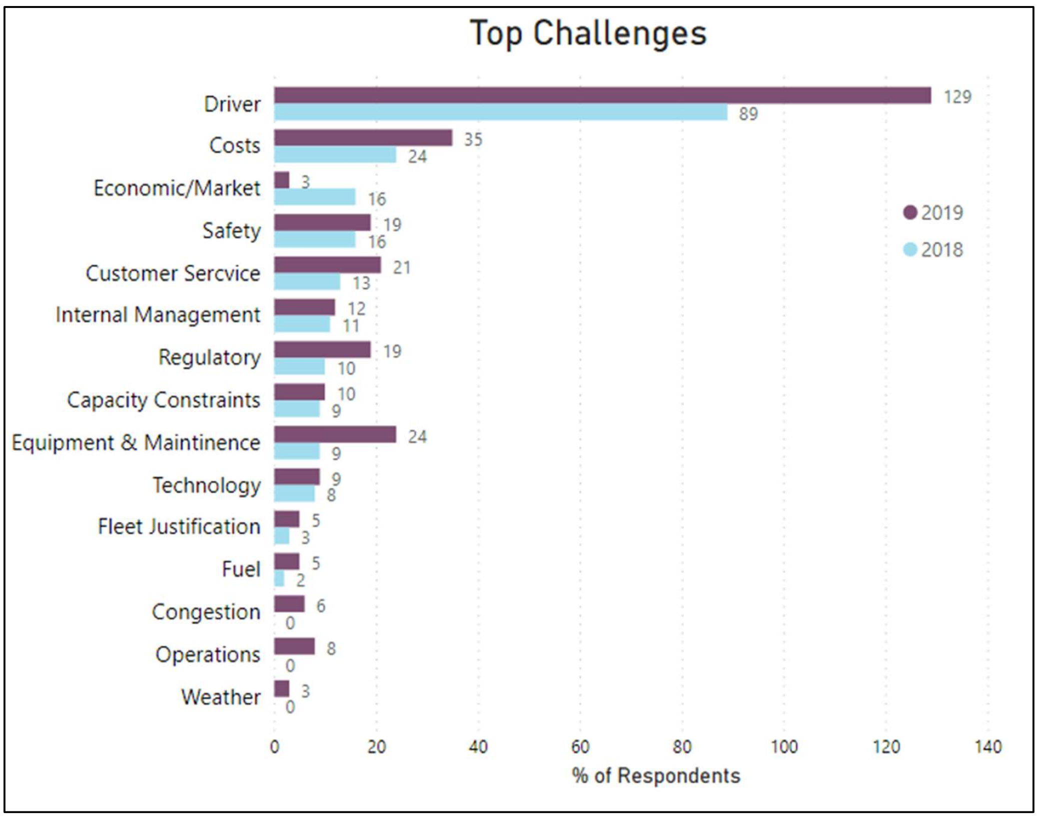
Existing literature can mostly be categorized into three groups: i) studies focused on driver utilization and addressing the shortage through better driver efficiency; ii) studies reporting on driver concerns and complaints and the impact on industry-wide driver retention; iii) studies on organizational impact and how the freight carrier can affect driver turnover and job satisfaction. While there is existing literature indicating that the relationship between freight carrier and driver may be important, little recent research has sought to quantify this relationship as we do by analyzing the impact of dispatchers on driver performance metrics.

2.1. *Driver Shortage*

The truck driver shortage is an acknowledged problem across the freight industry and is often cited as carriers' top industry concern. The "Critical Issues in the Trucking Industry" report from the American Transportation Research Institute listed the driver shortage as the most important concern among carriers for the past three years (ATRI, 2019). According to reports from the American Trucking Associations, the shortage was first reported in 2005 and has been growing since then. The growth in the deficit has been steady, with no significant progress made in finding a solution. In fact, the only improvements seen historically have been in periods of reduced demand and not because the industry was able to attract or retain a higher proportion of drivers. The ATA study estimates that by 2023 there will be a shortfall of over 100,000 tractor-trailer drivers nationally, potentially growing to a shortfall of over 160,000 drivers by 2028 (ATA, 2019).

A Benchmarking Survey Report, done by National Private Truck Council (NPTC) (2019), asked respondents to list the top three challenges that they currently face in their fleets. Drivers were mentioned by almost every respondent, as can be seen in Figure 2.1.

Figure 2.1
Top Challenges Faced by Private Fleets



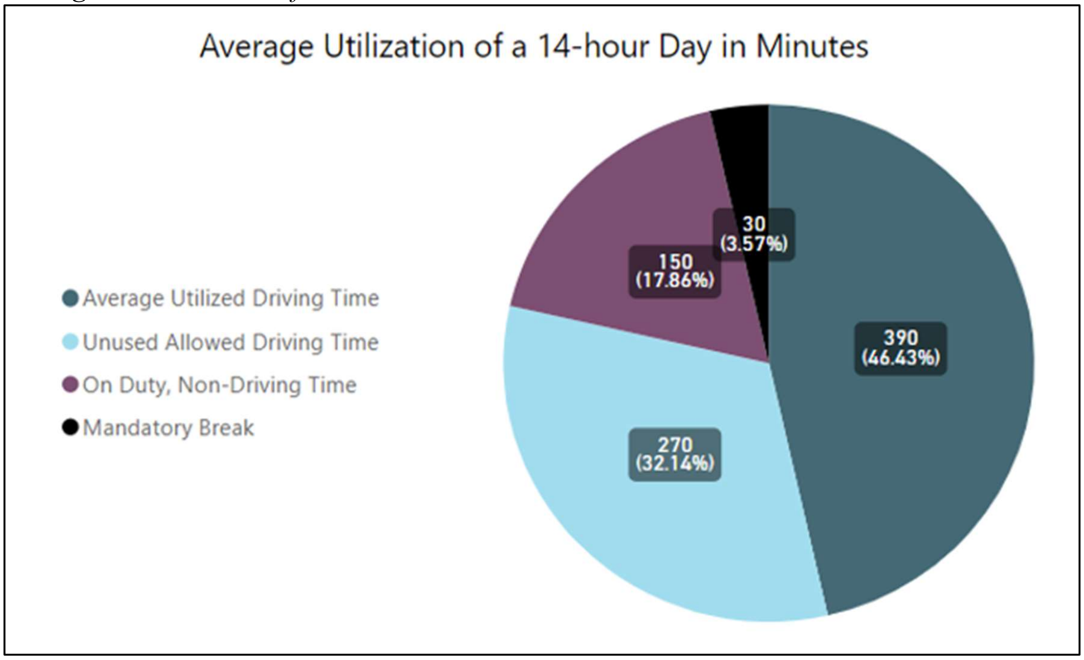
Note. Adapted from the National Private Truck Council [NPTC], 2019.

Compounding this issue is the additional requirement of compliance with the Drug and Alcohol Clearinghouse regulations. In 2016, the FMCSA passed a rule requiring State Driver Licensing Agencies (SDLAs) to check for drivers' past drug and alcohol violations before issuing, transferring, or renewing a Commercial Driving License (FMCSA, 2016). Previously, drivers terminated by a carrier for failing drug or alcohol testing would likely be blacklisted by that carrier, but free to seek employment as a driver with a different trucking firm. While this furthered the intra-industry churn of drivers, it did not lead to significant numbers of drivers leaving the industry. With the new regulation, drivers will be prohibited from driving for any carrier, unless and until they take remedial steps to reinstate their Commercial Driving License. Compliance with this law was mandated by January 2020 (subsequently delayed until 2023) and a Department of Transportation study estimates it could remove an additional 40,000 existing drivers from the workforce in the near future, likely exacerbating the ongoing driver shortage (FMCSA Drug and Alcohol Clearinghouse, 2020).

2.2. *Driver Utilization*

Despite the established shortfall in available drivers, studies indicate that existing drivers are not fully or optimally utilized. While HOS regulations cap drivers at 11 driving hours per day, studies find that OTR truckers are only able to take advantage of an average of 6.5 hours of driving (D. Correll, 2019). This low utilization of driving hours is often caused by drivers using these hours for other, non-driving, activities. Drivers must spend a portion of their time waiting, queuing, and loading/unloading at customer freight stops. These other activities are part of a driver's responsibility but are unpaid time and limit a driver's ability to maximize his paid time on the road as shown in Figure 2.2.

Figure 2.2
Average Utilized Time of Driver HOS



Note. Adapted from J.B. Hunt Transport, 2015.

This inefficiency is echoed by truck drivers' responses to a survey conducted by the American Transportation Research Institute & Owner-Operator Independent Driver Association Foundation (2020). When asked about what new policies, regulations, or exemptions state and federal governments should implement to address supply chain disruptions during national disasters (e.g. Coronavirus pandemic), 30% requested a relaxation or elimination of HOS regulations, and 10% requested the elimination ELDs completely. These responses suggests that the low utilization issue is related not to a driver's personal choice to drive fewer than the allowed hours but to unavoidable restrictions due to regulatory constraints (for example, non-driving activities that consumes drivers' duty hours).

The most time consuming of these non-driving duties is dwell, or the time a diver spends at customer freight stops waiting for goods to be loaded or unloaded. The American Transportation Research Institute found that "Detention/Delay at Customer Facilities" was ranked the fourth most important issue impacting OTR truckers in 2019, the first year the option was included in the survey (ATRI, 2019). While the need for additional drivers persists, much of the current literature agrees that even small increases in driver utilization of available hours would lead to a meaningful improvement against the driver shortfall (ATA, 2019). For example, Correll (2019) estimates that just an additional 12 minutes of driving per day could have counteracted the existing driver shortage at the time.

2.3. *Driver Reported Job Satisfaction and Impact on Turn*

Several studies have engaged directly with drivers to better understand their specific concerns and top complaints. Johnson et al. (2011) conducted a study examining the job satisfaction of long-distance truck drivers in the United States. With the goal of establishing the factors that determine job satisfaction in this occupation, they interviewed over 100 active drivers and summarized responses. The study found that 60% of drivers were not satisfied with their occupation and citied excessive time away from home and lack of respect for the occupation among their chief concerns (Johnson et al., 2011). Shattell et al. (2012) found, through a questionnaire issued to hundreds of active truck drivers, that while drivers generally rated their mental health as very good, when asked specific questions, many drivers confirmed suffering from these mental health issues. The summarized results found that 27.9% of drivers reported loneliness, 26.9% reported depression, and 14.5% reported anxiety (Shattell et al., 2012).

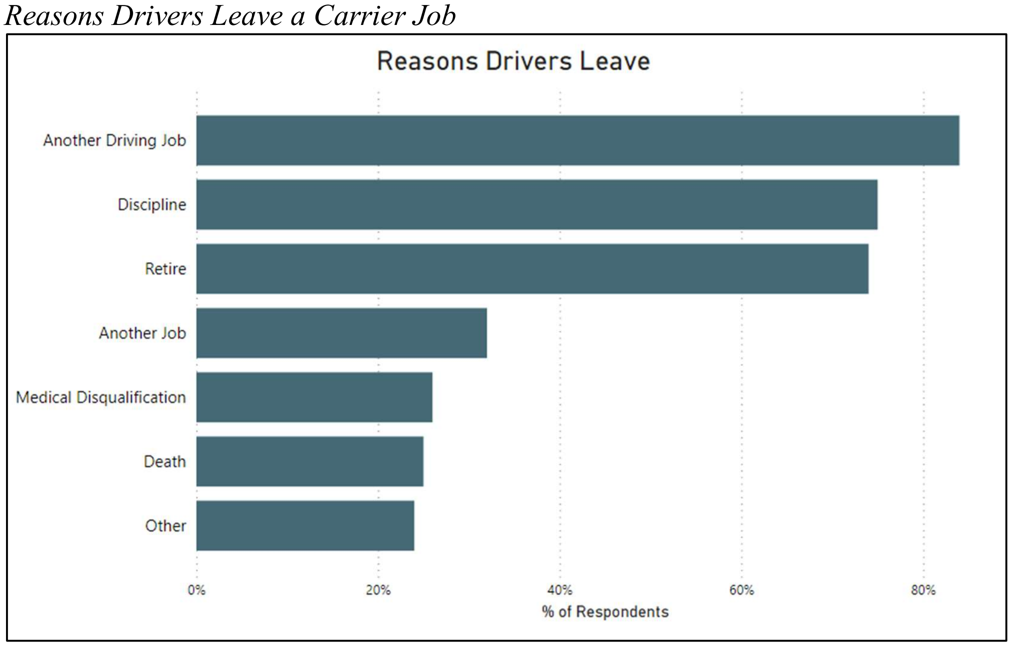
Studies such as these are often used to understand why drivers are leaving the industry of truck driving, a separate phenomenon from the internal industry churn. Burks and Monaco (2019) focused on the one-year occupational migration of truck drivers, found by comparing a baseline group of drivers to those still in the industry 12 months later. Though the study found that the number of drivers abandoning the industry was far smaller than the number of drivers moving between carriers, it also found that the true occupational migration rate for drivers was significantly larger than for workers with similar occupational requirements and demographics. After one year, 22% of drivers had left the freight trucking industry compared with 18% of other workers in similar occupations (Burks & Monaco, 2019)

2.4. *Impact of Dispatchers on Driver Retention*

In the trucking industry, it is generally accepted that high driver turnover is related to low pay and excessive time away from home. However, some literature suggests that these may not be the primary causes for a driver to quit. Keller and Ozment (1999) highlight that many drivers leave one firm for another that offers basically the same pay and working conditions. Figure 2.3 is adapted from the 2019 NPTC study and shows that the principal reason for a private fleet driver to leave a carrier is for a different truck driving role (NPTC, 2019). Richard et al. (1995) reasons that increasing pay, if economically feasible, may lead to more expensive turnover, and not necessarily lower turnover, since, in this competitive industry, a change in one company pay level would probably lead to changes in other companies as well.

Figure 2.3

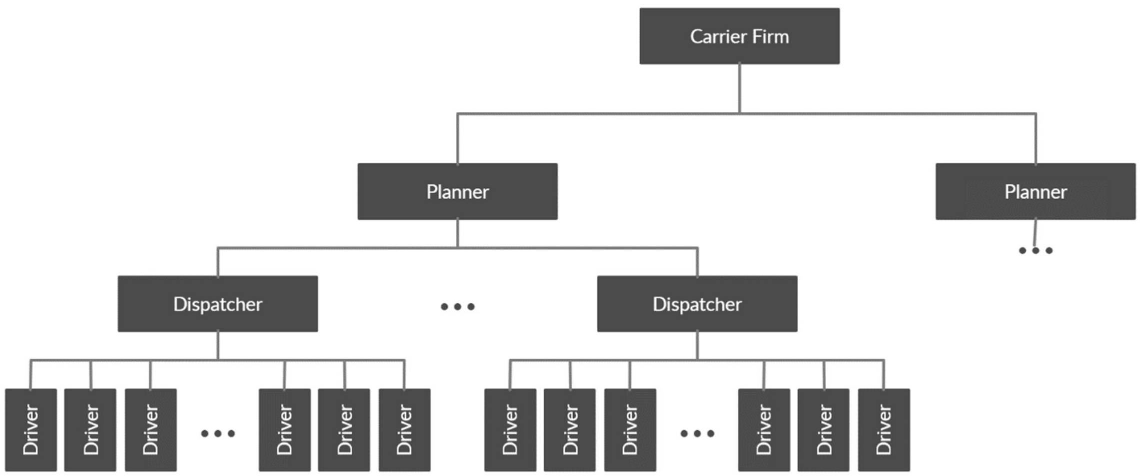
Reasons Drivers Leave a Carrier Job



Note. Adapted from NPTC, 2019.

Both these studies point out that dispatchers are an understudied factor that may have an important role on drivers' retention. Private fleets have, in general, one dispatcher for about 30 truck drivers (NPTC, 2019). While dispatchers may have the most direct communication and act as a driver's immediate supervisor, there is often higher levels of management responsible for load planning and routing. A typical carrier hierarchy is shown in Figure 2.4.

Figure 2.4
Traditional Hierarchy in Trucking Carriers



Dispatchers develop close relationships with drivers and could, potentially, better transmit policy changes to them and better represent the carrier firm. However, in general, these dispatchers lack supervisory skills, so they tend to avoid conflict and confrontation with drivers and many times choose to blame top management for company issues that may be causing drivers' dissatisfaction. This blaming may lead to a "dispatcher-driver versus management alliance that defeats the company's goal of keeping the driver" (Richard et al., 1995, p. 295). This finding was reaffirmed by Min and Lambert's later study which states that "the ongoing driver shortage is ... a symptom of poor driver management" and not due to economic factors (Min & Lambert, 2002, p. 14).

Arguing that dispatchers have the potential to contribute to a firm by first knowing drivers' concerns, Keller and Ozment (1999) suggest that firms concentrate on developing processes to increase dispatcher responsiveness to drivers. They conducted a study based on a theory known as Exit, Voice and Loyalty. The theory states that an employee, in this case a driver, has three ways to express dissatisfaction: i) exit: leave the company to work in another; ii) voice: stay and voice their concerns; and iii) loyalty: stay without voicing their concerns (a suffering stay). They concluded that greater responsiveness of dispatchers to drivers' voice and exit is associated with lower levels of driver turnover.

It is important to highlight that one of Keller and Ozment's (1999) hypotheses was not supported: higher levels of sensitivity to voice will be directly associated with lower levels of driver turnover. That is, sensitivity to voice without responsiveness does not necessarily contribute to driver retention. The study defends that dispatchers who respond more effectively to driver concerns have lower driver turnover rates. The study also incorporates the concept of Internal Relationship Marketing, stating that drivers can be seen as internal consumers. The main idea related to this is that the cost of gaining a new customer is much higher than the cost of retaining existing customers. Therefore, in this context, companies should seek and actively work to maintain long-term relationships with drivers.

The impact of working conditions and job satisfaction on driver retention was researched in Large et al. (2015). Though focused on European drivers, the description and value of the dispatcher/driver relationship mimics that of US OTR truck drivers. The study investigated seven interconnected hypotheses to determine what variables had the greatest impact on driver commitment. The authors identified two different types of commitment, occupational and organizational, which are each affected by different forces. Occupational commitment is defined as a driver's willingness to stay within the overall occupation of truck driving. This commitment is directly related to a driver's occupational satisfaction and is therefore too broad to be significantly impacted by an individual carrier. In fact, Large et al. (2015) speculates that the freight industry alone is unable to meaningfully change this commitment level and that only large-scale regulatory or political changes could increase drivers' occupational commitment and resolve the driver shortage.

Conversely, Large et al. (2015) defines organizational commitment as a driver's dedication to a particular carrier or employer. The power to change this level of commitment lies almost entirely within each individual trucking carrier. Additionally, Large et al. found that a vital element in a driver's commitment is the feeling of being supported by their employer. The perception of organizational support is in fact more highly correlated to increased organizational commitment than even overall job satisfaction. The study states "empirical investigations identify organizational support as a crucial factor of employment in the trucking industry" (Large et al., 2014, p. 67-68)

Interestingly, Large et al. (2015) questions whether it is beneficial to carrier organizations to improve the working conditions of their drivers, stating "it is doubtful whether the improvement of truck drivers' working conditions is in line with companies' individual business objectives" (Large et al., 2014, p. 71). However, there is significant opportunity for gain for companies who are better able to support their drivers, even beyond the obvious benefit of reducing driver turn. This supports elements of the Zhang and Buttgenbach (2020) study which addressed the poor utilization of driver hours. Zhang and Buttgenbach (2020) used driver ELD data and information of customer freight stops to assess factors leading to increased waiting or dwell time at these locations. Assuming that reducing dwell would lead to drivers being able to better utilize their allowed driving hours, increase their personal income, and mitigate the impacts of the driver shortage for their firm, Zhang and Buttgenbach (2020) found that drivers spent less dwell time at frequently visited freight stops and that frequency of visit explains 4.5% of dwell time variation. They therefore suggested that dispatchers could improve overall driver efficiency by relaying additional information when conveying load orders. Additionally, Zhang and Buttgenbach (2020) speculated that dispatchers could make better load planning and scheduling decisions by incorporating known wait times at specific facilities, again, allowing for more efficient use of driver time.

2.5. *Conclusion*

Though the value of dispatchers in the US freight trucking industry appears to be tacitly understood by researchers, few recent studies have focused expressly on their relationship to drivers and the impact it might have on driver retention and efficiency. By partnering with a midsized freight carrier, we employ data analytics to better understand this issue and find actionable insights into how this relationship can be leveraged to better support drivers. The goal is that this research will help mitigate the challenges the trucking industry faces from high driver turnover, low driver utilization, and the subsequent increasing driver shortage. While many studies have sought to understand this problem, a solution has yet to be found, so this area of study remains open for this capstone to explore.

3. Methodology & Data

The raw data used in this project was supplied by the mid-sized Midwestern carrier sponsoring the research. This carrier was able to provide detailed data on driver history, activity, and carrier hierarchy. To hone the quantitative analysis to the most relevant aspect of the freight industry, the raw data was cleaned and narrowed. Specifically, we limited the data to OTR truckers with assigned dispatchers to allow us to measure impact of carrier hierarchy on driver performance.

From the refined data, three performance metrics were defined that best represent individual driver performance and can be aggregated to measure dispatcher success. These metrics - utilization, efficiency, and retention - are relevant key performance indicators currently used by freight carriers in the US. Along with these metrics, several features were engineered that were later applied to the machine learning algorithms created to answer the key research question of how to explain the chronically low utilization and high turnover among over the road drivers.

3.1. *Description & Origin of Data*

The data and information used in this study comes primarily from our partnering company, the mid-sized freight carrier. This carrier has provided six months of data focused on three different areas: i) hours of service data for all drivers; ii) freight loading stops and the assigned dispatcher and the driver; iii) driver hire dates and terminations that occurred during this period. Available data covers May through October 2019, with a few exceptions noted below. Data is exclusive to OTR drivers and does not include dedicated contract business.

3.1.1. *Freight Plans and Stops*

The partnering carrier provided six months of customer freight stops organized by freight orders or "plans." This data provides the assigned customer and freight stop location for each plan as well as the driver who completed the job, the dispatcher that managed it, and the planner who assigned it. The dataset includes nearly 60,000 unique plans, of which 50,000 were completed by a solo driver (not a team). This represents 1,110 unique drivers, supervised by 59 dispatchers (referred to as Fleet Leaders), and 10 driver planners (referred to as Team Leaders).

The Freight Stop dataset identifies stops by type and whether the driver was required to wait for loading or unloading to be completed. The Freight Stop dataset is not complete: it contains only the loading stops at the beginning of each freight plan but does not contain the final unloading stops. The dataset therefore is principally used for pairing Fleet Leaders to drivers so that driver performance can be aggregated to the dispatcher level. This process is described in more detail in section 3.3.

3.1.2. *Driver Hours of Service*

In addition to the Freight Stop data, the partnering carrier has made available Electronic Log Data (ELD) for all drivers, in a report of driver Hours of Service (HOS). The HOS dataset is the largest made available for this study, with over 1.6 million rows of data. Covering the same May through October 2019 period, the data shows a driver's full activity, including the time spent and distanced traveled in each activity block. Because ELDs are now mandatory for collecting drivers' hour of service data, this dataset is an accurate record of driver activity for the time period provided. Most importantly, this data will indicate the number of available driving hours that drivers are utilizing in each 14-hour workday.

3.1.3. *Driver Tenure*

One additional element of the data that was not previously available or studied is the tenure of each driver listed in the Freight Stop and HOS datasets. This data also includes a record of all driver employment terminations that occurred during the May through October 2019 period. These terminations include resignations (initiated by the driver), discharges (initiated by the carrier), retirements, and transfers. Of these terminations, over 94% (544) were due to either resignation or discharge. Separately, the partnering carrier has provided the hire date of all drivers who joined the company after January 1, 2010, whether they are still actively employed by the carrier, and if not, their termination date. This data allows for the inclusion of driver tenure as a factor in understanding our driver performance metrics.

The limitation of this data is that it is only possible to measure a driver's time with this carrier, and not in the truck driving profession overall. Additionally, the carrier has specified that while drivers with hire dates prior to 1/1/2010 are employed by the company, those employees' specific hire dates are not available. Therefore, all measures of tenure can only be calculated to an approximately 10-year maximum (12/31/2010 – 10/31/2019, the last date of available HOS and Freight Stop data).

3.2. *Constraints and Relevancy of Available Data*

The partnering carrier was able to provide six months of data, the maximum time span maintained in their system records. Maintaining six months of data is standard practice for US freight carriers as FMCSA requires a minimum of six months retention period for driver logs. The May through October 2019 period represents all the data available at the time that the initial request for data was made, late in 2019.

Though data for a half year period should offer enough volume and variability to be generalizable, it does exclude seasonality as a possible factor in any analysis. The data provided by the partnering carrier does not include some of the traditionally heaviest months for freight trucking demand, around the US holiday period. Though this study does not attempt to capture the impact of seasonal demand on the success of truck drivers, future researchers may choose to apply the methodology introduced here to a broader set of data and include this factor.

Notably, the data provided by the partnering carrier precedes any impact from the current COVID pandemic in 2020. Since the pandemic became a national concern in the US in the first quarter of 2020, there has been a steep increase in the demand for freight movements for essential products and, consequently, for truck drivers. To address this increase in demand, the FMCSA relaxed both HOS regulations and oversight in March of 2020 (ATRI & OOIDA, 2020). This relaxation of the binding regulations allowed greater flexibility of time to the now even more essential truck drivers. While the COVID impact has been significant globally, it will hopefully be temporary, and the US will soon revert to standard HOS restrictions and more predictable freight trucking demand. Though the data used in this study is now over a year old, as it fully excludes the pandemic's impact, it may prove to be more relevant and generalizable to the future of US truck driving than more recent data.

3.3. *Data Processing and Cleaning*

To exclude non-relevant data and outliers, the datasets were processed and cleaned according to the needs of this study and the parameters set by the partnering carrier. Though the original datasets already excluded dedicated contract drivers, the HOS data was further filtered to exclude Independent Contractors and Driver Teams. While team driving does exist, it is a less common practice in the freight industry and therefore the focus of this study is limited to solo OTR drivers. Independent Contractor drivers are not employed by carriers in the traditional sense and so were also removed from the data.

Because this capstone hypothesizes that dispatchers have a significant and unexplored impact on the success of individual drivers and the carrier firm, the Freight Stop dataset was used to pair drivers and Fleet Leaders (dispatchers). Any drivers who drove 80% or more of their freight plans with a single dispatcher during the May to October timeline were "assigned" to that dispatcher. The majority of drivers (50%) drove under a single dispatcher's oversight, with 76% of the remaining drivers meeting the 80% margin. Drivers who did not meet this standard, and dispatchers who had no assigned drivers, were removed from the data.

The partnering carrier also established reasonable ranges for several of the variables included in the provided data. From the Freight Stop data, any driver stops with a duration shorter than 15 minutes or longer than eight hours were excluded. Fifteen minutes was determined to be too little time for an active stop, meaning there would not have been adequate time for a true freight collection. Stops longer than eight hours were identified by the partnering carrier as driver rests and not required freight stops, so were similarly excluded.

The individual datasets were then concatenated and aggregated into tables, breaking out performance by driver. Once aggregated by driver performance, any drivers who did not fall within the reasonable rage for miles driven in six months were removed. This removed any drivers with an average driving miles per day on duty greater than 770 which would represent the extreme case of driving the full allowable 11 hours at 70 miles per hour. Once these drivers were removed, a similar concatenation and aggregation process was applied to find aggregate dispatcher performance. Once cleaning and aggregation were complete, two refined datasets remain, Driver Performance and Dispatcher Performance, with the volume of data included shown in Table 2.

Table 2
Final Dataset and Key Variable Size

HOS dataset lines	1,017,346
Freight Plans and Stops dataset lines	49,985
Drivers	621
Dispatchers	21

3.4. *Metrics and Measures*

In the freight industry, several different metrics are used to measure driver performance and quantify success. According to the partnering carrier, a dispatcher is considered successful if the group of drivers he oversees achieves a competitive number of miles traveled and a higher-than-average retention rate. Therefore, utilization, efficiency, and retention are the key metrics used in this capstone to measure dispatcher performance. In addition to these dependent variables, this study captures other factors that relevant literature has defined as valuable to driver experience, profitability, and quality of life, such as weekends worked, consistency of work, and perception of support from the carrier firm (Large et al., 2014).

3.4.1. *Performance Metrics*

In freight trucking, utilization can be understood as a distinct metric from efficiency, though both are critical to the profitability of an individual driver and the carrier firm. Because drivers are capped by federal law from driving more than 11 hours in a 24-hour period, utilization is based on how many of these available driving hours drivers actually use. This pure utilization metric can be calculated as $\frac{Driven\ Hours}{11\ Allowable\ Hours}$. Current studies show that drivers are only using 59%, or 6.5 hours, of the allowable 11 hours of driving (D. Correll, 2019).

In addition to utilization, it is important to understand driver efficiency, which can be measured in cumulative on-duty miles driven. On-duty driving is associated with the normal work of a driver and is distinguished from any miles driven outside of the requirements of a customer freight order, and include both active freight orders and what the industry refers to as “deadheading” or driving the tractor trailer without hauling any goods. These activities are different from the less-frequent off-duty driving which occurs outside of normal work (typically final distances to return home, etc) Miles driven measures not just a driver’s activity, but also his personal profitability and his monetary value to the carrier firm. The driver efficiency metric can be calculated as the average miles driven per day on duty, $\frac{Miles\ Driven}{Days\ On\ Duty}$.

Driver retention is a perennial concern in the truck driving industry, which continues to battle a driver shortage and near-continuous driver turnover (ATA, 2019). Though most of the turnover is inter-industry churn, the cost of replacing and training new drivers is significant, with studies estimating the cost as at least $2,000 to $5,000 per driver (Suzuki, 2007). Retention can be measured as one minus the ratio of driver terminations compared with the total number of drivers employed during the study or

$$1 - \frac{Driver\ Terminations}{Drivers\ Employed\ During\ the\ Study}.$$

3.4.2. *Feature Engineering*

In addition to performance metrics, several features were calculated to be used in further data analysis and machine learning. These independent variables are dimensions of the data that have a correlative and potentially causal relationship with the performance metrics of individual drivers and dispatcher groups. Key features and what they represent are listed in Table 3.

Though related to driver retention (the measure of keeping drivers) the concept of tenure (the measure of a driver's length of employment) is a separate and unique feature. While retention is a performance metric, or dependent variable, tenure is an independent variable that can be used as a feature in understanding the characteristics of a successful dispatcher or driver. There is little current research that uses tenure as a determining factor in driver retention or performance, so this variable may prove crucial to understanding these aspects of carrier success. As noted, the available data only shows hire dates historical to 1/1/2010, and therefore the maximum tenure we can confidently state is approximately 10 years - from 1/1/2010-10/31/2019 (the last date of available driver activity data).

Simple features, such as cumulative days on duty, total miles driven, and total plans worked, form the basis for performance metrics and other engineered features. Days on duty sums any date during the six-month dataset when the HOS data for a single driver included either a "driving" or "on duty" work status. One challenge faced is that HOS restrictions apply to 24-hour periods and not traditional working days. In order to calculate days on duty and other time-based features, each line of HOS data, and therefore the hours of each activity, was assigned to the calendar date on which that activity ended. For example, if a driver drove for six hours beginning at 10pm on June 1, 2019, the full 6 hours of driving would be counted towards the June 2, 2019 total.

This conversion allowed for the merging of 2019 calendar data into the research dataset. With this addition, weekday could be included as an analysis feature. This is most relevant for calculating the number of weekends worked and the ratio of weekend days worked to all days on duty. In a similar fashion, the number of Mondays worked and their ratio to all days on duty were calculated. Though not overtly studied previously, there is a pervasive industry assumption that drivers wish to spend weekends at home with their families and not on the road, working. Additionally, it has been historically challenging for dispatchers to find drivers willing to accept Monday assignments (perhaps because it is the day drivers must leave their families). This study explicitly tests these theories.

Team size is a dispatcher specific feature which calculates the number of drivers that each Fleet Leader managed for the duration of the available data. Though there is significant variation in the team sizes for the dispatchers studied, the average team size is roughly 28 drivers. One goal of this research is to determine whether there is an optimal number of drivers that an individual dispatcher can manage to maximize performance metrics.

Table 3
Key Engineered Features

Feature Name	Description
Efficiency	Average total miles driven per day on duty
Utilization	Ratio of hours driven of the allowable 11 HOS
Retention	Ratio of retained drivers to the total drivers employed during the six months of available data
Total Miles Driven	All driven miles recorded in the HOS data per driver
Days on Duty	Count of days with either a "driving" or "on-duty" status line in HOS data per driver
Mondays % of All Days on Duty	Ratio of Mondays to all days on duty
Weekends % of All Days on Duty	Ratio of Saturdays and Sundays to all days on duty
Tenure	Duration of employment with the partnering carrier, to a 10-year maximum
Tenure Class	Binary variable – whether a driver is in his first year of employment with the partnering carrier
Team Size	The number of drivers managed by an individual Fleet Leader (dispatcher)
CV of Freight Miles	Coefficient of variation in the distribution of freight miles to drivers within a dispatcher team
CV of Freight Plans	Coefficient of variation in the distribution of unique freight plans to drivers within a dispatcher team
Rehired	Binary variable – whether a driver was terminated and rehired by the partnering carrier
Average loading dwell	Average loading dwell time per day on duty
Dispatcher %	Ratio of freight plans driven under a driver's main dispatcher
Unique Dispatchers	Count of unique dispatchers who managed freight plans for a single driver

3.5. *Analysis and Investigation*

To demonstrate the impact of carrier dispatchers on driver success metrics, this study utilizes a combination of methods, including regression models and unsupervised machine learning algorithms. The analysis shows that dispatchers have a meaningful impact on individual driver performance and distills managerial insights that can be applied by carriers to improve fleet performance. It should be noted that this study does not attempt to generate an equation to predict driver performance or retention in the future; it only analyzes and explains current performance.

The initial analysis used unsupervised machine learning to cluster dispatchers over the available features and aggregate driver performance into a small number of distinct groups. As an unsupervised algorithm, clustering avoids, as much as possible, any unintentional user bias in the outcome. With K-Means clustering, distinct groups were generated with obvious tradeoffs in performance across the key metrics. These groups were then considered in further analysis to understand how management techniques might differ and drive variances in driver performance.

Regression analysis quantified the independent variables which have the greatest impact on the dependent variables, the driver success measures of utilization and efficiency. (Because of its binary classification per driver, retention was only explored as a part of the clustering algorithm.) From the combined and aggregated Driver Performance and Dispatcher Performance data sets, several variables were found to be valuable in the linear regression analyses. These variables included features from the raw data as well as the calculated features described above. The regression models quantify the effects of variables as coefficients against the baseline level of success (the intercept) for each metric and provide p-values for each coefficient to quantify validity. While Classification and regression tree (CART) algorithms were also applied, they did not reveal any additional or different features of value. Because of the decision to not pursue a predictive model but instead a descriptive model with clear managerial insights, the CART analyses were ultimately discarded. Using multiple models allowed for different key features to surface and broaden the overall understanding of the most impactful variables.

The methodology employed in this study allowed for the analysis of the relationship between truck drivers and dispatchers. It further identified the characteristics of this relationship that impact the success of a driver. The findings reveal actionable insights that carriers can employ to improve driver hour utilization and retention.

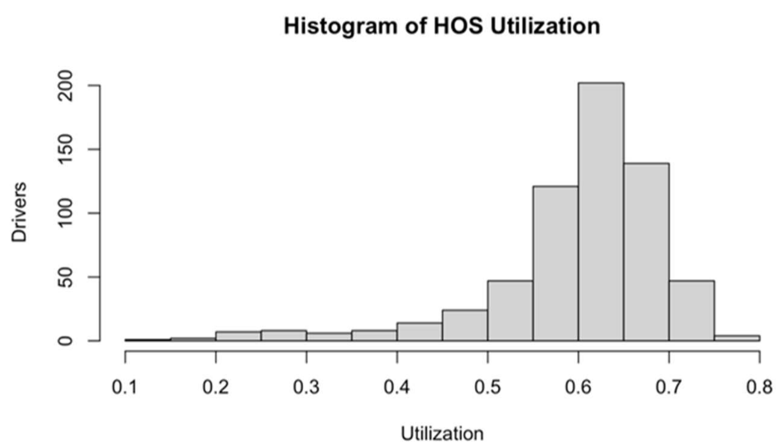
4. Results

From the final dataset of 621 drivers, descriptive statistics were first explored for the three key metrics. Histograms were also generated to display and analyze distribution patterns. Next, the three key metrics were plotted against variables initially thought to be impactful, to see if any patterns emerged. After this exploratory phase, clustering and machine learning algorithms were utilized to identify features and quantify their impact on the key variables. These results allow for insights on how carriers use dispatcher management techniques to improve the performance of their fleet drivers.

4.1. *Performance Metrics and Frequency*

Performance in utilization was measured as the per driver average hours driven, as a percentage of the 11 driving hours allowed by HOS regulations. The drivers in the final dataset had a range of 65%, from a minimum utilization of 15% to a maximum of 80%. The mean performance was 60%, or 6.6 hours. The Figure 4.1 histogram shows the slight right skew of the distribution of utilization and Table 4 shows the descriptive statistical values.

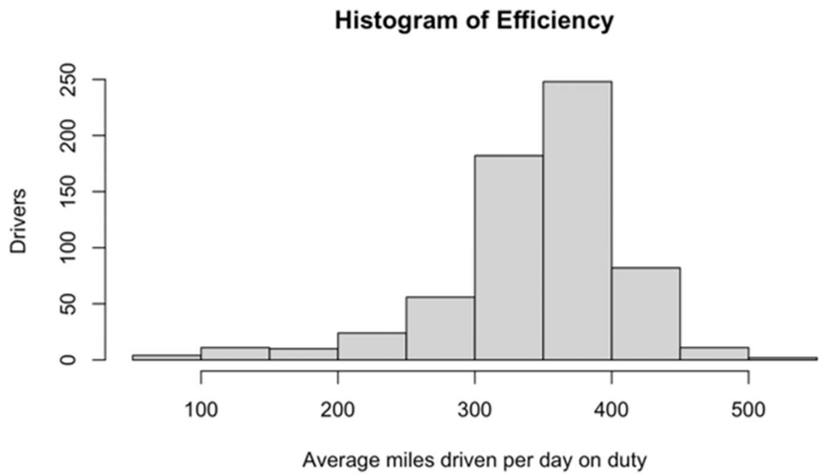
Figure 4.1 & Table 4
Driver HOS Utilization Histogram and Descriptive Statistics



minimum	14.82%
mean	60.04%
median	62.08%
maximum	79.62%
range	64.80%

Like utilization, efficiency performance (drivers' average number of miles driven per day on duty) follows a slightly right skewed distribution. The mean performance is 345 miles per day with a range of 444 miles between the maximum of 527 and the minimum of 83. The histogram in Figure 4.2 shows this right skewed distribution of drivers' average performance and Table 5 shows the key statistical values for efficiency in the driver dataset.

Figure 4.2 & Table 5
Average Miles Driven per Day on Duty Histogram and Descriptive Statistics



minimum	82.94
mean	345.00
median	355.31
maximum	526.67
range	443.73

Because retention is a binary conditional for each driver, the same statistical analysis could not be performed. Instead, a histogram of driver tenure was created showing that over half of all drivers employed by the partnering carrier during the studied time had been employed for 10 years or more. Because hire dates prior to January 1, 2010 were not included in the data, the analysis could not be more precise. Figure 4.3 shows the distribution of driver tenure.

Figure 4.3
Histogram of Driver Tenure

4.2. *Initial Feature Analysis*

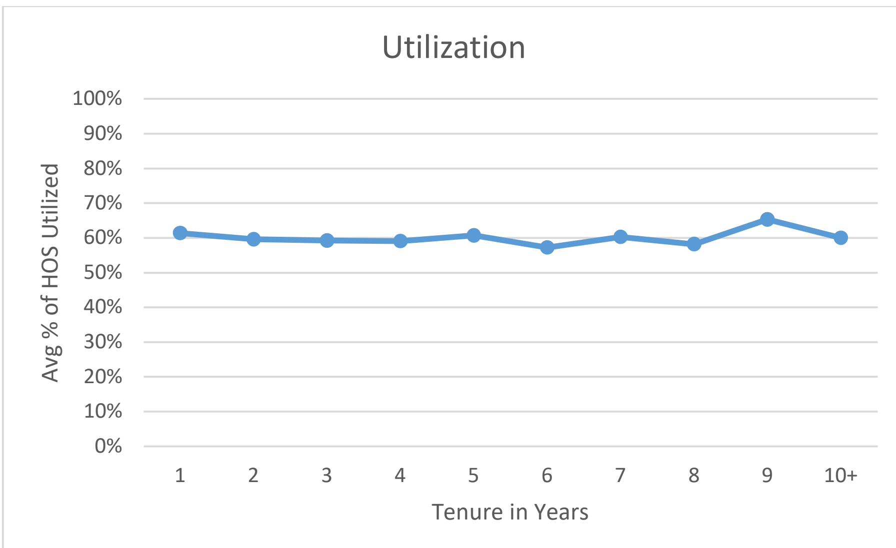
Prior to applying any machine learning to the structured datasets, a visual analysis was completed by plotting the three key performance metrics against several of the engineered features. The most compelling results came from the graphing of driver utilization, efficiency, and retention against Fleet Leader team size and driver tenure. The initial results, described in detail below, led to linear regression analyses to verify if the patterns observed visually were statistically significant.

4.2.1. *Utilization, Efficiency, Retention by Driver Tenure*

Utilization, efficiency, and retention metrics were graphed against driver tenure by grouping drivers by years of employment with the partnering carrier. For example, a driver in his second year of employment would be grouped in year two. Due to data limitations, drivers grouped in year 10 include any drivers with more than 9 full years of employment with the partnering carrier.

Figure 4.4 shows that there is little variability in utilization when compared with driver tenure, with all drivers averaging near the industry-wide average of 59% of the 11 hours of driving allowed under HOS regulations, found by D. Correll, 2019. Though generally flat, there is a small increase in utilization among the year nine drivers, though with only five individuals in this category, this may not be statistically significant. Figure 4.4 shows the flat performance of approximate 60%, or 6.6 hours, utilization across driver tenure groups.

Figure 4.4
Utilization by Driver Tenure



Efficiency graphed by driver tenure follows a similar pattern to utilization. There is a peak in efficiency performance with the drivers in their ninth year of employment with the carrier. These drivers see a roughly 12% improvement from the baseline of approximately 350 miles per day to reach a high of 398 average miles per day on duty, as seen in Figure 4.5. Again, the increase in year nine should not be considered conclusive, as with only five drivers in this group, it is not substantial enough to generate reliable conclusions. Like utilization, efficiency performance is mostly flat when graphed against driver tenure.

Figure 4.5

Efficiency by Driver Tenure

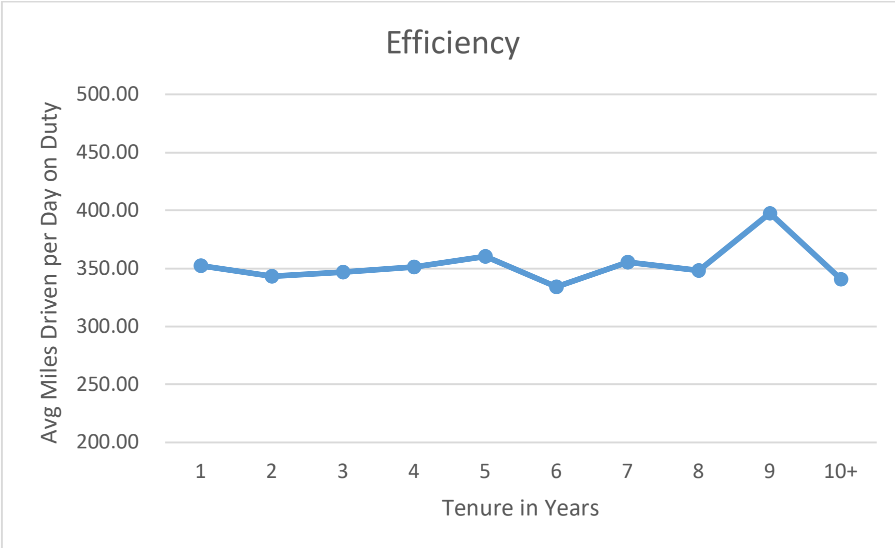
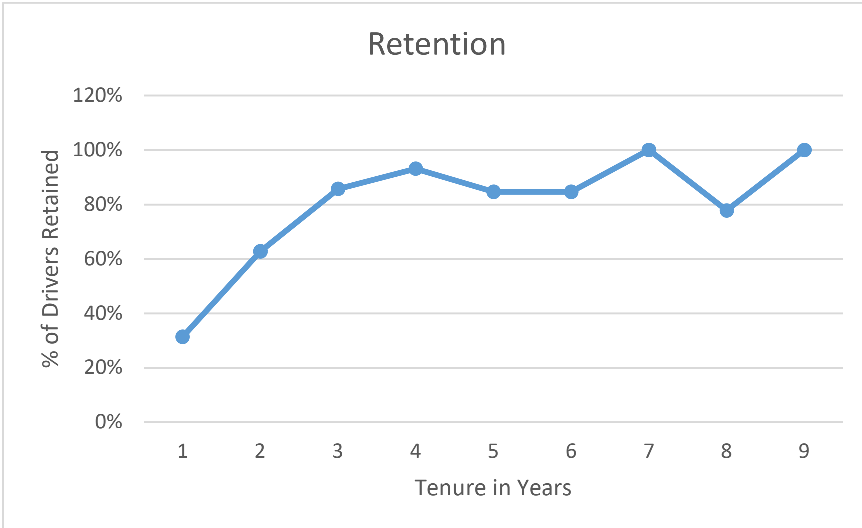


Figure 4.6 displays driver retention as a function of tenure. Here, drivers with 10 or more years of employment were excluded. Because of the nature of the data, this group exclusively contains drivers still employed by the partnering carrier at the end of the provided dataset and therefore offers no valuable insights. Figure 4.6 shows that newer drivers are more likely to leave the carrier. First year drivers have a retention rate of only 31%, which increases steadily with tenure, reaching a high of 93% in year four. Year five marks a turning point, as aggregate retention decreases 9% to 85%, where it remains through year six. More tenured drivers then display sporadic performance, swinging from 100% in years seven and nine to the much lower 78% in year eight.

Figure 4.6
Retention by Driver Tenure



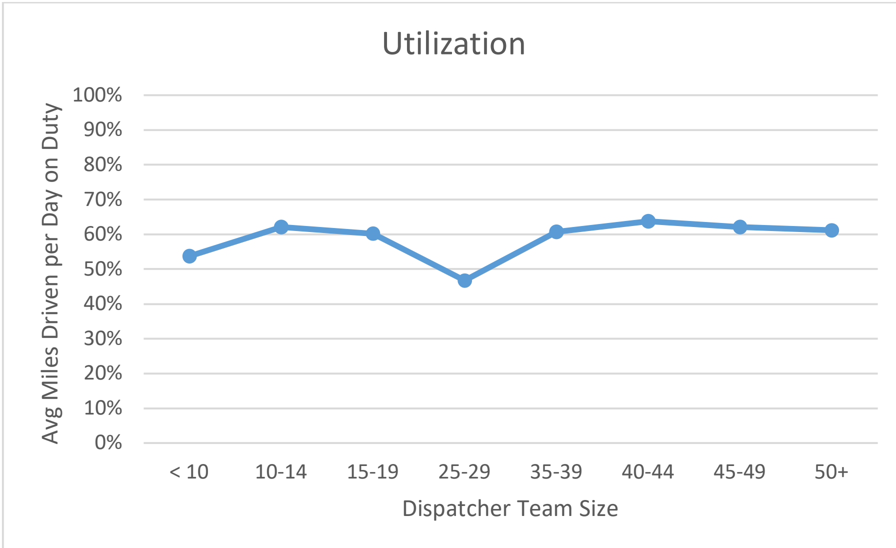
4.2.2. *Utilization, Efficiency, Retention over Team Size*

Utilization, efficiency, and retention metrics were also graphed against Fleet Leader team size to see if there were any correlations between the number of drivers managed by a single dispatcher and those drivers' aggregate performance. Drivers were classified based on the total number of drivers managed by their assigned dispatcher. The eight categories are intervals of five, beginning with very small teams of fewer than 10 drivers, up to the very large teams of 50 or more drivers.

As with tenure, utilization is mostly flat across all team sizes with a noticeable dip in performance in team sizes of 25-29. Here, the utilization is only 47% (5.17 hours), 22% below the average performance of 60% as seen in Figure 4.7.

Figure 4.7

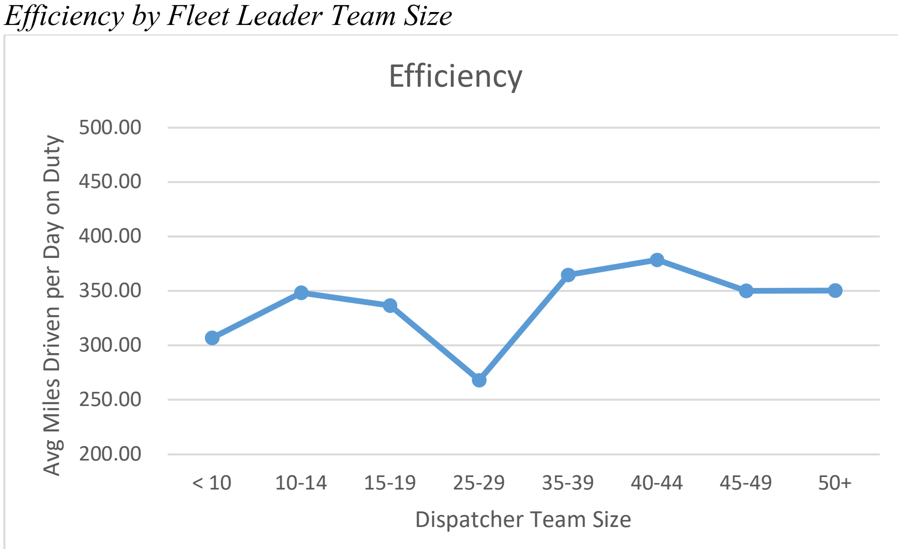
Utilization by Fleet Leader Team Size



Efficiency as a function of team size follows the same pattern but is even less consistent than utilization. Figure 4.8 shows an upwards trend in performance as team size grows, with notably low performance in teams sized 25-29. This group performs 27% worse than similar teams with an average of only 268 miles per day on duty (compared with 356 for team sizes of 35-39). There is no obvious cause for this decrease, so it requires further investigation to explain whether it is significant and what the impact is for freight carriers.

Figure 4.8

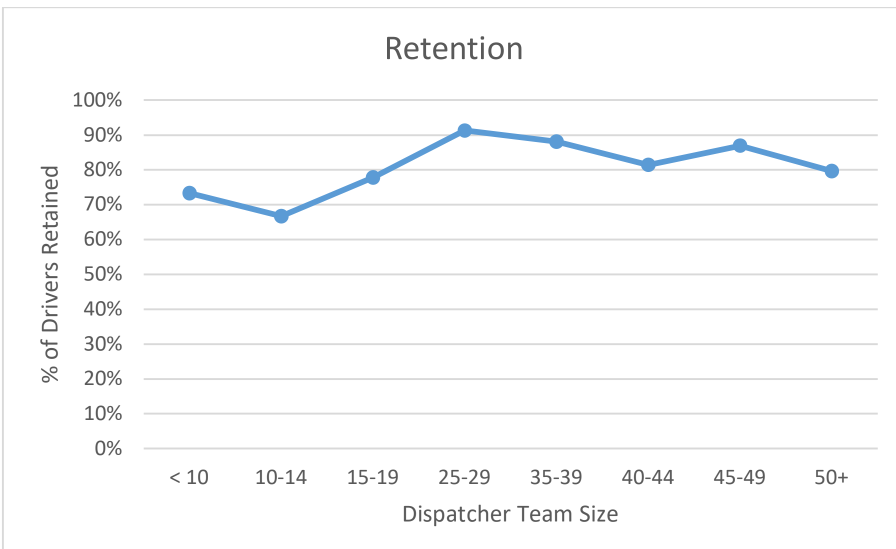
Efficiency by Fleet Leader Team Size



Lastly, retention was charted as a function of team size, displaying a new pattern of performance. In Figure 4.9 we see retention rate peaking in the same team size category (25-29 drivers) where utilization and efficiency dipped. Here, the lowest retention rate occurs in dispatcher teams of fewer than 15 drivers. As team size increases, so does retention before peaking as the industry average team size of 30 drivers is reached. Teams larger than 30 show slightly lower but relatively steady performance. This implies that retention may not correlate with efficiency or utilization and may follow different trends.

Figure 4.9

Retention by Fleet Leader Team Size



4.3 Dispatcher Clustering

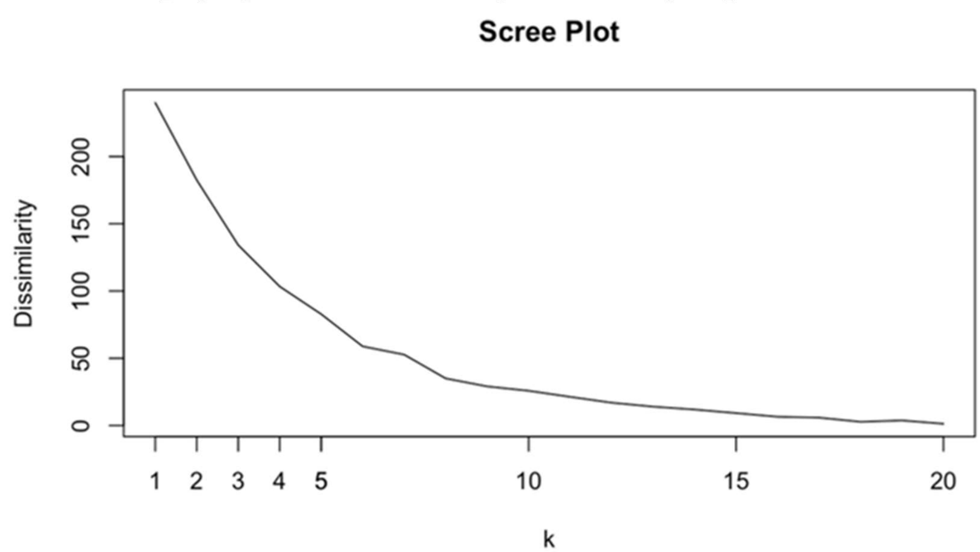
To determine whether individual dispatchers behave in classifiable ways, unsupervised machine learning was used to cluster the 21 dispatchers over a series of metrics and features. Using R to complete a K-means clustering program, the dispatchers were grouped according to their performance in 12 key variables, shown in Table 6.

Table 6
Features Used in Clustering

Variables Used	
Average driver utilization	Average loading dwell time
Average driver efficiency	Rehired driver (binary)
Driver retention	CV in miles assigned to drivers
Dispatcher team size	CV in plans assigned to drivers
Total miles driven	Ratio (%) of Mondays worked
Total plans driven	Ratio (%) of weekend days worked

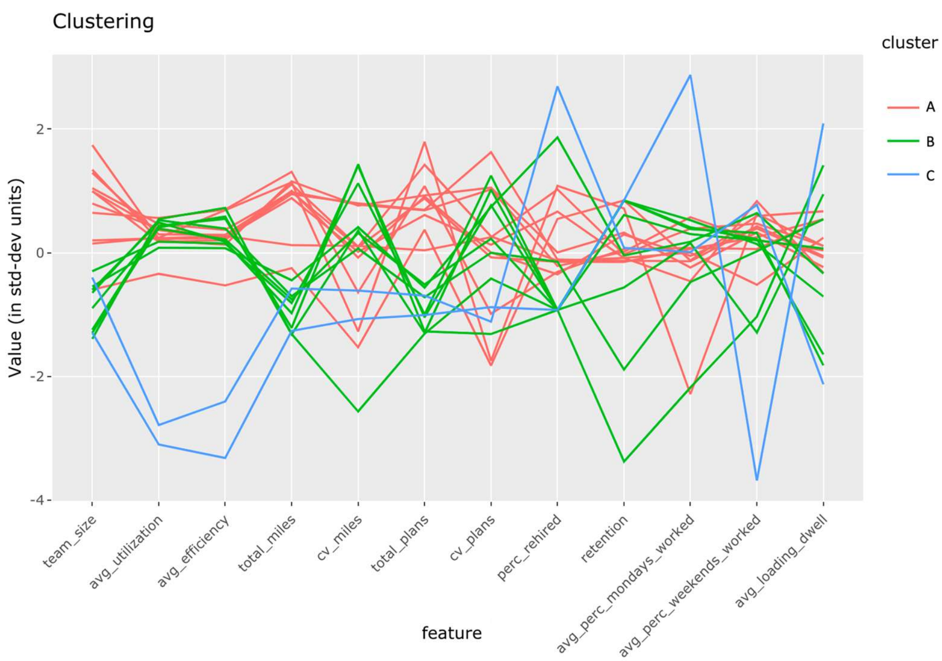
One limitation of K-Means clustering is that the number of clusters, or "means", must be chosen manually. To find the best division of dispatchers, a Scree Plot was used per the description in the Bersimas, et. al text *The Analytics Edge* (Bertsimas et al., 2016). The Scree Plot graphs the level of variance within each cluster against different numbers of clusters. As seen in Figure 4.10, as the number of clusters grows, the dissimilarity within each group decreases with a natural limit of no variance with 21 clusters of just one dispatcher each. Typically, the ideal number of clusters will be found in the "elbow" of the graph or at the inflection point when both variance and number of clusters can be minimized. For this study, this falls between three and five means.

Figure 4.10
Scree Plot Displaying Cluster Variance Against Count of Dispatcher Clusters



To minimize variance, the clustering algorithm was first run with five means. However, with a total of only 21 dispatchers, five clusters did not generate groupings capable of providing meaningful insights, including clusters with a single dispatcher. The same was true when running the algorithm with four means. Running the same algorithm using three means created clusters with 11, eight, and two dispatchers, as seen in Table 7, and reasonable homogeneity in behavior across features, as seen in Figure 4.11.

Figure 4.11 & Table 7
Dispatcher Clusters

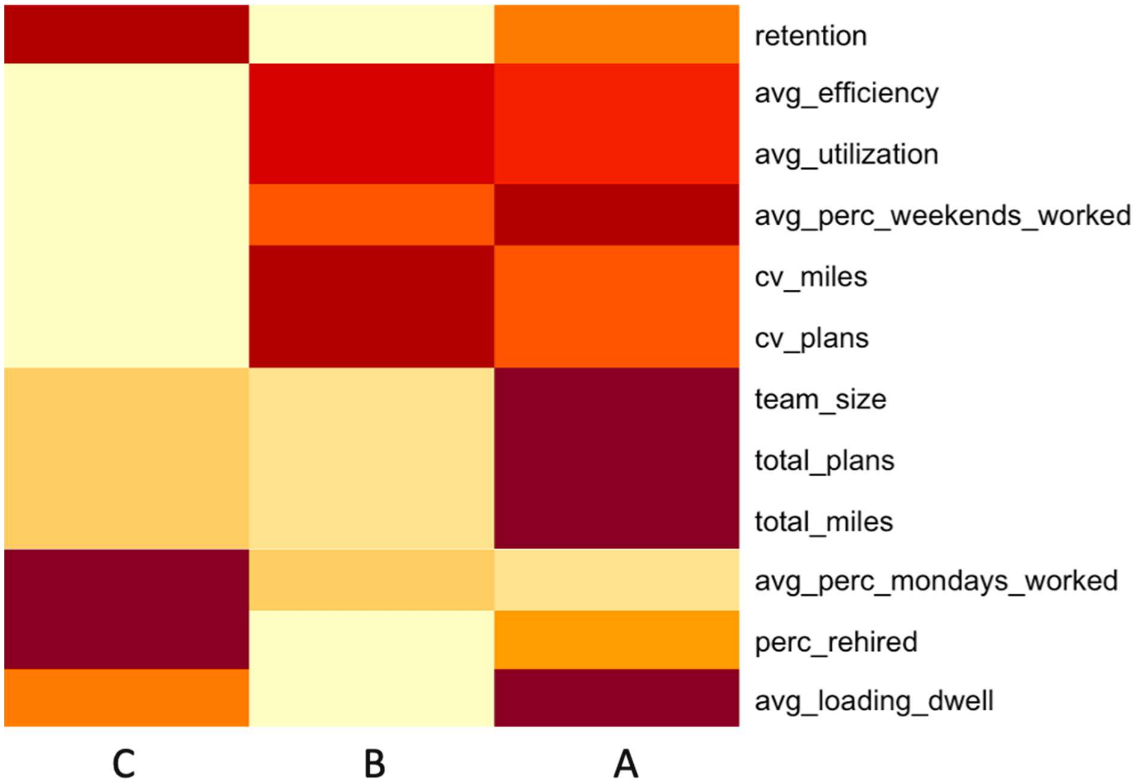


Cluster	Number of Dispatchers
A	11
B	8
C	2

In addition to grouping dispatchers, the clustering algorithm charts each cluster's relative performance in the included features. The output reveals that there are significant differences in how each cluster of dispatchers performs in the key metrics of efficiency, utilization, and retention. The varying performance in other clustering features indicate that decisions in driver management lead to deltas in these key metrics. Figure 4.12 shows which cluster scores highest (darker color) on each feature and metric.

Figure 4.12

Comparative Performance of Dispatcher Clusters



The feature clustering supports the assertion that dispatchers are indeed impactful in driver performance and that tradeoffs in performance must be made by carrier management. Specifically, it is clear that while utilization and efficiency are closely linked in performance, retention is a separate metric that is not correlated. The correlation matrix in Figure 4.13 displays how closely each feature correlates with the others. It is clear from this matrix that utilization and efficiency are highly positively correlated, as one increases so does the other. Retention, alternatively, does not trend with the other key metrics, meaning that it behaves differently and is likely impacted by different features. The matrix also reveals other, highly correlated features including:

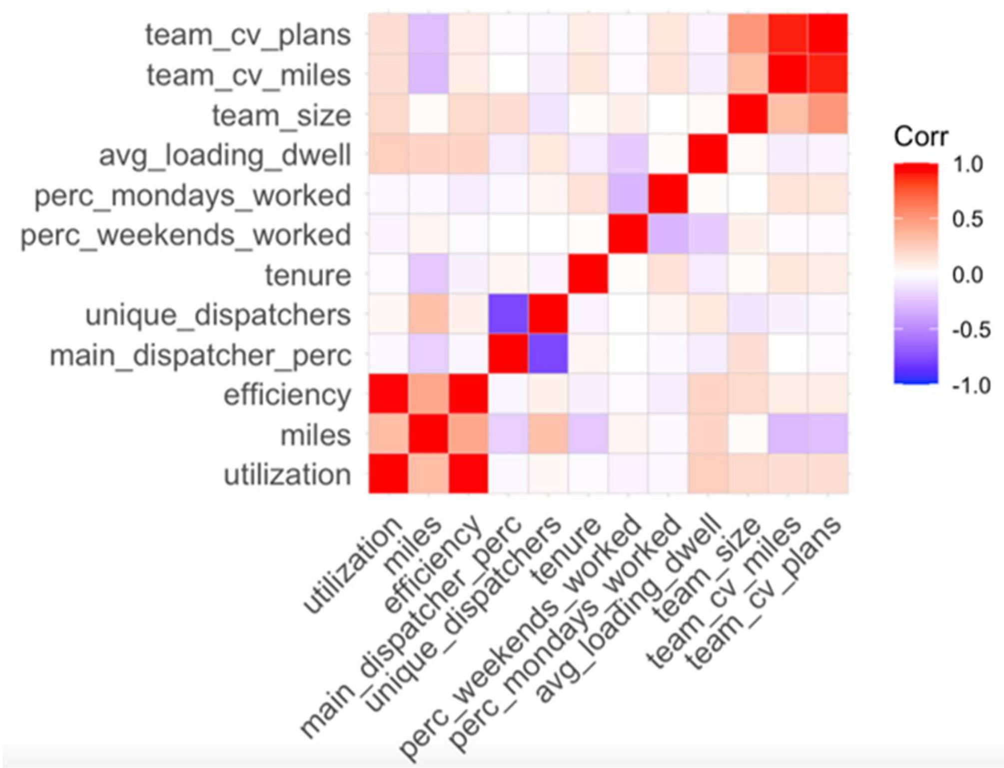
- Coefficient of variation of driver plans and coefficient of variation of driver miles, which quantifies how equally dispatchers assign work to the drivers they manage

- The ratio of freight plans a driver worked under his main dispatcher compared to the number of unique dispatchers he worked under
- Total miles driven against the key metrics of efficiency and utilization.

Because of the high correlation, one of each pair of highly correlated features was removed from the final regression algorithm to avoid increasing random error, or "noise", in the models.

Figure 4.13

Correlation Matrix for Features Used in Clustering



4.4. *Linear Regression Modeling*

Identifying which features are most impactful on key metrics allows for further investigation into how dispatchers may influence those features. For utilization and efficiency metrics, this feature identification is best achieved through linear regression models. Linear models capture linear relationships between the independent variables (features) and dependent variables (key metrics). The statistical significance of each feature is then quantified with a p-value, or probability value.

4.4.1 *Utilization*

The linear regression model for driver hour utilization was first performed across all engineered features of individual drivers. Total miles driven was excluded because of the high correlation with the performance metrics of efficiency and utilization, as noted above. The resulting model had an Adjusted R-squared value of 0.1803, meaning that the features included explain roughly 18% of the variation in driver hour utilization. Furthermore, the model identifies the features with the most statistically significant impact, or lowest p-vales, as identified in with asterisks in Figure 4.14

Figure 4.14
Initial Linear Regression Results - Utilization

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          7.605e-01  1.456e-01   5.225 2.38e-07 ***
main_dispatcher_perc -1.498e-01  1.309e-01  -1.144  0.25306
unique_dispatchers   -1.350e-02  1.140e-02  -1.184  0.23699
tenure               -2.429e-06  3.318e-06  -0.732  0.46445
tenure_classold       2.856e-03  1.268e-02   0.225  0.82183
rehired1             -4.529e-02  1.395e-02  -3.245  0.00124 **
perc_weekends_worked -7.677e-03  5.552e-02  -0.138  0.89007
perc_mondays_worked  -1.203e-01  1.055e-01  -1.139  0.25501
avg_loading_dwell     8.992e-02  1.615e-02   5.567 3.87e-08 ***
team_size            -3.020e-03  6.327e-04  -4.774 2.26e-06 ***
class_team_sizesmall -1.503e-01  2.111e-02  -7.118 3.05e-12 ***
team_cv_miles         1.502e-01  5.763e-02   2.607  0.00936 **
team_cv_plans         7.942e-02  6.134e-02   1.295  0.19589
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08912 on 617 degrees of freedom
Multiple R-squared:  0.1959,    Adjusted R-squared:  0.1803
F-statistic: 12.53 on 12 and 617 DF,  p-value: < 2.2e-16
```

The linear regression was then rerun including only those features identified as being statistically significant. Two of the features, average loading dwell and coefficient of variation in the distribution of miles, positively impact utilization, meaning that as these coefficients increase, utilization is expected to improve. The remaining two features, whether a driver was rehired and whether a dispatcher's team has fewer than 30 drivers, negatively impact utilization. This means that dispatchers with larger teams and fewer rehired drivers perform better in aggregate than the comparison group. All four features have very low p-values, indicating that they are statistically significant in impacting the dependent variable of utilization of HOS hours. When considered jointly, these features have an R-squared value of 0.1525, meaning that they explain approximately 15.25% of the variation in driver utilization, as seen in Figure 4.15.

Figure 4.15

Final Linear Regression Results – Utilization

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)           0.499209   0.018780  26.582  < 2e-16 ***
rehired1             -0.042148   0.013433  -3.138  0.00178 **
avg_loading_dwell     0.096594   0.015874   6.085 2.03e-09 ***
class_team_sizesmall -0.054530   0.008619  -6.327 4.77e-10 ***
team_cv_miles         0.114019   0.025521   4.468 9.39e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09062 on 625 degrees of freedom
Multiple R-squared:  0.1579,    Adjusted R-squared:  0.1525
F-statistic:  29.3 on 4 and 625 DF,  p-value: < 2.2e-16
```

That these features are determinant in utilization indicates that there are managerial impacts on driver performance. Drivers who are a part of larger dispatcher teams with less equally distributed freight miles have higher utilization performance. Though only a small portion of the drivers studied, several drivers were terminated or resigned and then rehired by the partnering carrier within the time period examined. This negative impact of the "rehired" feature means that drivers who were rehired had lower utilization than their counterparts. This could be due to lower productivity drivers being terminated but later rehired, possibly as the carrier experienced a driver shortage. Lastly, though longer loading dwell time is a key feature of higher utilization, this may be a misleading finding. It is more likely that as drivers take on more freight plans, and therefore experience more loading stops overall, they utilize more of the available HOS.

4.4.2 *Efficiency*

Like with utilization, the initial linear regression model for efficiency was run on all available features. This model generated an R-squared value of 0.1589, meaning it explains approximately 16% of efficiency variance. This initial regression also revealed critical features impacting efficiency, or average miles driven per day on duty. The p-values and coefficients of these features can be seen in Figure 4.16.

Figure 4.16
Initial Linear Regression Results – Efficiency

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)          4.360e+02  9.707e+01   4.491 8.45e-06 ***
main_dispatcher_perc -6.603e+01  8.730e+01  -0.756  0.44972    
unique_dispatchers   -2.287e+00  7.606e+00  -0.301  0.76375    
tenure               -3.894e-03  2.213e-03  -1.760  0.07895 .  
tenure_classold       7.980e+00  8.454e+00   0.944  0.34557    
rehired1             -2.982e+01  9.306e+00  -3.205  0.00142 ** 
perc_weekends_worked  7.119e+00  3.703e+01   0.192  0.84761    
perc_mondays_worked  -1.158e+02  7.039e+01  -1.644  0.10059    
avg_loading_dwell     4.741e+01  1.077e+01   4.401 1.27e-05 ***
team_size            -1.936e+00  4.219e-01  -4.588 5.42e-06 ***
class_team_sizesmall -1.004e+02  1.408e+01  -7.131 2.80e-12 ***
team_cv_miles         8.689e+01  3.844e+01   2.261  0.02413 *  
team_cv_plans         3.501e+01  4.091e+01   0.856  0.39247    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 59.44 on 617 degrees of freedom
Multiple R-squared:  0.1749,	Adjusted R-squared:  0.1589 
F-statistic:  10.9 on 12 and 617 DF,  p-value: < 2.2e-16
```

An additional regression was then run on only the identified significant features. Like with utilization, CV of the distribution of miles and average loading dwell time were positively impactful for efficiency. Small team size and whether drivers were rehired were again negatively impactful. Because utilization and efficiency are so highly correlated, it is likely that the same features are impactful in the same ways. In addition, a new feature, ratio of Mondays driven, was identified as a critical feature with negative impact on efficiency. Taken together, these five features explain approximately 13% of the variability in miles efficiency (R-squared value of 0.1274), as seen in Figure 4.17.

Figure 4.17
Final Linear Regression Results – Efficiency

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)           319.854     14.618  21.880  < 2e-16 ***
rehired1              -24.940      8.975  -2.779  0.00562 ** 
perc_mondays_worked  -135.052     67.257  -2.008  0.04507 *  
avg_loading_dwell      53.423     10.612   5.034 6.28e-07 ***
class_team_sizesmall  -38.176      5.767  -6.619 7.79e-11 ***
team_cv_miles          46.369     17.206   2.695  0.00723 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 60.54 on 624 degrees of freedom
Multiple R-squared:  0.1344,	Adjusted R-squared:  0.1274 
F-statistic: 19.37 on 5 and 624 DF,  p-value: < 2.2e-16
```

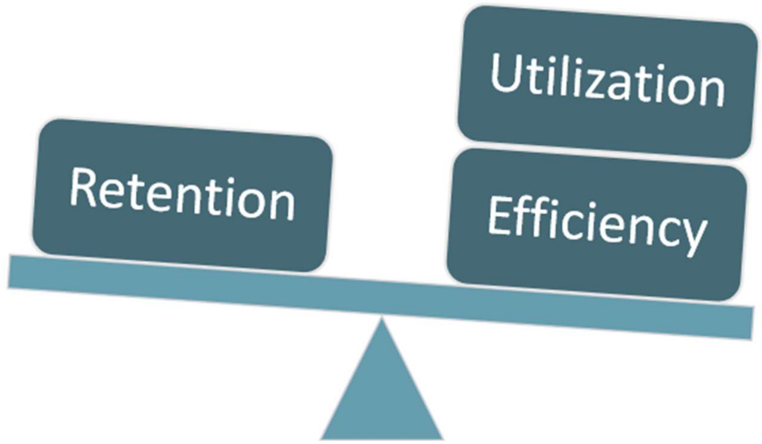
5. Discussion

As the results revealed, there are distinct classes of dispatchers with varying performance across the three key metrics of hour utilization, miles driven per day on duty, and driver retention. These differences indicate that decisions made by dispatchers in the management of their drivers led to tradeoffs in driver performance metrics. The regression analyses revealed that there are at least three levers that carrier organizations can use to improve their aggregate driver performance across the metrics of utilization, efficiency, and retention.

5.1. *Managerial Insights*

The central takeaway from clustering dispatchers across the features and key metrics is the inherent tradeoff between performance in utilization, efficiency, and retention. While utilization and efficiency trend together, retention behaves rather differently, as demonstrated in Figure 5.1. It is the dispatchers with the lowest aggregate retention that perform best in the other two metrics. Though retention is a crucial focus of the freight industry, especially in mitigating the driver shortage, it may not be the most important consideration. If we consider the driver shortage as not just a lack of available drivers but instead a shortage of available driver hours, utilization actually becomes a more important metric. This is especially true in the context that most driver turnover is actually intra-industry churn, meaning that the industry as a whole is not losing a large number of drivers to low retention (Gallup Organization, 1997).

Figure 5.1
Visual Demonstration of the Inherent Tradeoff in Driver Performance



One can best understand the different clusters of dispatchers in the context of a well-known children's story, "Goldilocks and the Three Bears". As in the story, the dispatcher classes can be compared to the chairs found in the Bear Family home: the too soft chair of Mama Bear, the too rigid chair of Papa Bear, and the "just right" chair of Baby Bear. Class C, where retention is highest, but utilization and efficiency are low, is most analogous to Mama Bear's chair. The dispatcher has created an environment where drivers are more likely to stay with the carrier but do not contribute as much as other driver groups. Class B is comparable to Papa Bear's chair, where productivity is highest, but retention is very low. Finally, there is the "just right" Class A with the most dispatchers and balanced performance in all three key metrics, meeting high utilization and efficiency while also maintaining a relatively high retention rate.

The results also indicate that there are different driver profiles, which may respond differently to management techniques. Effective management would tailor their techniques to best meet the needs of these driver profiles; this would likely improve driver productivity and willingness to stay with that carrier. Drivers would also be better served if carriers recognized their differences, increasing their sense of organizational support and ability to earn money. The clustering makes it clear that some dispatchers are already taking this personalized approach to management through the distribution of freight plans. The results reveal that freight plan distribution is just one of at least three levers that carriers can use to impact the key metrics of driver performance. The levers include the CV of plans/miles distribution, weekdays driven, and dispatcher team size. Though these levers exist, the tradeoffs indicate that carriers may have to reevaluate what is most valuable for their firm and where to place the fulcrum to balance the three key metrics.

5.1.1. *The Importance of Weekday*

The first managerial lever is the concept that day of the week matters to driver performance. Notably, we found that drivers driving more Mondays perform worse in the key metric of efficiency. Though the impact of weekday on driver productivity has long been anecdotally understood in the trucking industry, the linear regression shows that this trend is indeed true. Mondays are seen as challenging days for drivers (and for dispatchers to find willing drivers), as they typically represent the first day that a driver must leave his home and family to go back out on the road. The results indicate that drivers who are driving less frequently on Mondays, and who therefore are likely not following a standard Monday-Friday workweek, drive more miles per day on average. These drivers may have more flexible schedules and are therefore more likely to accept freight plans, increasing their efficiency. Understanding how a driver prioritizes his time could allow dispatchers to more easily assign freight plans on these "difficult" weekdays to the drivers more willing to accept them. This would increase both aggregate driver performance and a driver's sense of organizational support, if he feels his personal needs are met along with his professional ones.

5.1.2. *Variation in Distribution in Freight Plans and Miles*

The second managerial lever is the variations in assigning freight plans and miles within a dispatcher group. The coefficients of variation in miles and plans measure how equally a dispatcher divided up freight plans and assigned miles amongst the drivers he manages. From the clustering and regression analyses, it is clear that this variability is highly correlated with the three key metrics of utilization, efficiency, and retention. Class C (Mama Bear) has the lowest variation between driver plans and miles and also maintains the highest retention. However, this class also shows the lowest utilization and efficiency, implying that there may be some value to the unequally dividing workload.

Conversely, Class B (Papa Bear) has the highest CV of plans and miles, meaning the dispatchers may be assigning work only based on driver capability - where the more efficient driver receives even more opportunity. However, drivers in this class also have the lowest retention, perhaps as drivers become frustrated with the unequal distribution of work. The largest class, A (Baby Bear) seems to be the most balanced, both leveraging the value of assigning work by ability or interest while still maintaining longer driver retention, and ostensibly a more content driver group. The dispatchers managing these groups may form stronger relationships with their teams and be able to better utilize the strengths of individual drivers or may be fostering greater driver investment through healthy competition. The differences in performance between the dispatcher classes could be better understood with additional insight from dispatchers and drivers.

5.1.3. *Impact of Team Size*

Originally, it was thought that smaller dispatcher teams might operate more effectively. Because dispatchers are the link between drivers and carriers, there was an early assumption that dispatchers with smaller teams would better understand the needs and adapt to concerns from their drivers, leading to higher driver productivity and retention. Instead, the linear regression model revealed that team size is positively related to efficiency and utilization, meaning that drivers on larger teams actually perform better in these metrics. Crucially, we also found that team size is highly correlated to CV of both miles and plans. This indicates that larger teams actually provide dispatchers more flexibility to assign freight plans and distribute load miles. With more pieces to move, dispatchers may be able to create more efficient and productive plans for their teams and provide drivers with the schedules that best suit their strengths and needs.

5.2. *Future Applications*

While this study has yielded meaningful results and implications for managing carrier fleets moving forward, there is still more to be investigated on this topic. This capstone represents one of the first attempts to quantify the impact of carrier dispatchers on the key driver metrics of utilization, efficiency, and retention, so opportunities remain to build on this work. Specifically, a larger, more detailed, or broader dataset could reveal even more key features among drivers and dispatchers that explain the low utilization and high turnover of drivers today. Additionally, due to some data limitations, several key metrics could not be incorporated here, but might reveal more incisive conclusions if used in a similar study.

5.2.1. *Opportunities for Broader Datasets*

The biggest limitation of this study was the relatively small size of the dataset. After cleaning, just 21 dispatchers were left to feed into clustering and regression algorithms. Though meaningful insights were distilled from this data, machine learning algorithms typically work best with large datasets on which to train and cluster. A similar analysis to the one performed here, applied to a larger group of dispatchers, may reveal clearer patterns, stronger correlations, and additional conclusions.

Additionally, the data provided for this study was limited to six months. This is the standard timespan of data saved by carriers and is long and large enough to be generalizable. However, this dataset explicitly excludes the US holiday season, which is typically the heaviest for over the road trucking. Additionally, by being limited to only half a year, the data did not allow for seasonality as a feature in the analysis. Seasonal changes in trucking demand, weather patterns, and shipment type may prove to be a valuable feature in predicting or addressing trucker performance in the future.

5.2.2. *Opportunities for the Inclusion of Additional Features*

The data used in this project was focused on driver behavior and therefore contains few features related directly to the dispatchers. Specifically, tenure data, while valuable, was only made available for drivers, not dispatchers. Additional information about dispatcher history or experience could prove informative if included in future analyses such as this one.

One element of this study that we were unable to pursue was the inclusion of qualitative interviews with both dispatchers and drivers. Though quantitative analysis can reveal patterns and critical components in data, these findings can lose impact without context. Aspects of dispatcher performance that the data cannot capture are the relationship between the dispatcher and his drivers, his management techniques, and the practices he uses. Though we were able to cluster dispatchers into distinct groups and assume that this means that there are distinct business practices pursued by each class, we do not know what those differences are.

It would be valuable to understand how each dispatcher approaches his work and what impact that has on his managed drivers. Interview questions could be created to leverage and contextualize findings from the analyses including the variables identified as having the greatest impact on driver success that are actionable by dispatchers. For example, this study shows that there is value in unequally distributing freight plans to drivers but does not reveal what a dispatcher considers when making these determinations. This could be based on past driver performance or features such as driver tenure. Furthermore, it would be beneficial to speak with drivers and hear directly what the most important elements of their relationships with dispatchers are, especially when considering that the driver's perception of support is such an important determinant in retention, per Large et al. (2015).

5.2.3. *Opportunities for the Inclusion of New Performance Metrics*

Because the dataset used in this study did not contain unloading stop data, additional metrics could not be calculated or utilized. To measure efficiency, this study uses total miles driven per day on duty; however, a more accurate metric could be applied instead. While total miles driven measures the volume of travel drivers complete over time, it is more informative to measure loaded miles (miles carrying goods). "Deadheading," or driving the tractor trailer without hauling any goods, is a regular part of driver responsibilities, like dwell time. However, deadhead miles are less financially valuable to both drivers and carrier firms. Ideally, when measuring efficiency, one would include only loaded miles, calculated as the miles traveled between collection and drop-off of goods as part of a customer freight plan.

Additionally, the exclusion of unloading events forced the exclusion of dwell time when calculating driver hour utilization. Decreasing dwell time could be one opportunity to increase driver hour utilization, as literature suggests that it is not driver choice to drive fewer hours but is instead is due to other requirements of the driver's job eroding these available driving hours (Zhang & Buttgenbach, 2020). In addition to the 11-hour driving capacity, HOS regulations set a driver's total workday capacity at 14 hours, including a 30-minute mandated break. Under these constraints, any additional non-driving job functions that exceed 2.5 hours a day in fact reduce the driving hours available to that driver. Therefore, the true utilization calculation should not have a denominator of the 11 allowable hours, but instead the available hours, or 13.5 working hours less the time spent in dwell. The calculation for this Dwell Adjusted Utilization is as follows: $\frac{Driven\ Hours}{Min(13.5\ Working\ Hours - Hour\ \ of\ Dwell, 11\ Allowable\ hours)}$. Comparing the traditional utilization measure to the Dwell Adjusted Utilization measure should provide a clearer picture of the restrictions under which drivers operate and offer an additional lever for improving driver hour utilization.

6. Conclusion

There is a saying: "If you bought it, a truck brought it!" This captures the expanse and impact of the $800 billion American trucking industry, which moves 72.5% of all US freight (ATA, 2020). Yet despite being so crucial to the US economy, the freight industry faces several compounding challenges - driver shortage, low driver utilization, and high driver turnover. The driver shortage, estimated to reach 160,000 driver short by 2028, is exacerbated by the under-utilization of driver HOS hours and the frequent driver employment turn. While several previous studies, both at MIT and beyond, have attempted to explain and resolve these chronic industry issues, none have fully succeeded. Recognizing a gap in the research, this study focused on analyzing the impact of carrier dispatchers on truck driver performance across the three key metrics of driver utilization, efficiency, and retention.

Unsupervised clustering found that there are distinct dispatcher classes, analogous to Goldilocks' three bears, managing drivers with different techniques. The differences in both aggregate performance and feature use indicate that decisions made by dispatchers in the management of their drivers leads to tradeoffs in key performance metrics. While utilization and efficiency are highly correlated, retention is not, meaning that dispatchers who maximize productivity tend to have lower driver retention. Though retention has long been a key concern in the freight industry, these tradeoffs indicate that it may not be the only consideration. Carriers may have to better understand their objectives - whether productivity or retention is most conducive to their business growth - before determining how to best manage their drivers. Defining the driver shortage not by insufficient individuals but as insufficient driver hours could allow a carrier to justify higher driver turn if maximum productivity is extracted during that shorter employment.

Additionally, the clustering and regression algorithms revealed that a finite number of features have a direct and meaningful impact on driver productivity. These features clearly indicate that there are specific managerial levers that can be used in the management of drivers to improve overall fleet performance. The levers of freight plans/miles distribution, weekdays assigned to drivers, and dispatcher team size all fall within the control of the carrier and its dispatchers. The variation in performance further indicates that some dispatchers may be aware of different driver profiles and may already be taking a more personalized approach to the management of those drivers. The “Baby Bear” class of dispatchers have been able to successfully balance the productivity of their drivers (in efficiency and utilization) with the need for driver retention. This study has opened the door to the concept that carrier organizations themselves can mitigate the problems facing the freight industry. Most importantly, it indicates that dispatchers are more than just administrators: they are perhaps the lynchpin linking driver and carrier goals.

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