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Empirical Study Of Basic Violations, Pay Incentives, And Safety: Evidence From U.s. Intrastate Carriers

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EMPIRICAL STUDY OF BASIC VIOLATIONS, PAY INCENTIVES, AND SAFETY: EVIDENCE FROM U.S. INTRASTATE CARRIERS

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Chapter 1 INTRODUCTION

Background

The trucking industry is one of the most critical industries in the U.S., mainly due to the contribution to the US economy. According to Bureau of Transportation Statistics (BTS), transportation and utilities counted 5.3% of the civilian labor force in 2016, and nearly 11.7 trillion worth of goods (in 2012 dollars) are transported by trucks in 2015, which accounts for 61% of the total value transported in that year (Michael J Sprung, 2018). The number of for-hire carriers totaled 892,078 in May 2019, according to the Federal Motor Carrier Safety Administration (FMCSA). One may expect such a large industry to be concentrated and led by a few large firms, like in railroads and airlines. However, 90% of the carriers operate six or fewer trucks in 2018, suggesting the small carriers are the dominating force in the industry.

Scholars believe the highly segregated market is the consequence of the Motor Carrier Act (MCA) in 1980, which breaks the barriers to entry. In economics, the deregulation effectively promoted market competition and dramatically affected driver's compensations. (Michael H. Belzer, 1994, Barry T Hirsch, 1988, Barry T Hirsch et al., 1998, Barry T. Hirsch, 1993, Kristen A. Monaco and Taggert J. Brooks, 2001, Nancy L. Rose, 1987). Like each coin has two sides, there are winners and losers of such a policy change, as Dr. Belzer stated in his book *Sweatshops on wheels:* winners and losers in trucking deregulation: "…the consumers are better off with the lower rates and truck drivers are worse off with low pay, long hours and unsafe and unsanitary conditions”(Michael H. Belzer, 2000).

In the classic supply and demand model, if more firms enter the market, then the supply will shift outward, and that drives the equilibrium price down. For a profit-maximizing carrier, it will receive a maximized profit when it sets the driver's wage as the same as the price of the transportation service. If the price is down due to market competition, that means a driver’s wage will decrease accordingly. However, this static model fails to tell the external consequences of the decline in drivers’ compensation. Presumably, one big concern is the impact of compensation on drivers’ safety.

In the past two decades, various studies have shown the relationship between pay incentives and driver’s safety. Monaco and Williams use data from the 1997 Survey of 573 truck driver interviews conducted by the University of Michigan, a.k.a. The University of Michigan Trucking Industry Program (UMTIP). Each interview took about 40 minutes to finish, in which questions were regarding compensation, demographics, use of logbooks, attitudes toward Hours of Service (HOS) Regulations, and others at the truck stop. Five years later, they provide details on sampling methodology and statistics in their book *Sailors of the Concrete Sea* (Dale Belman et al., 2005), which was the summary publication of descriptive data from this dataset. Using the UMTIP cross-sectional data, they estimated the relationship between three safety measures and driver characteristics and found that less sleeping and more mile driven would both increase the probability of violating the logbook (one of the common HOS violations). Also, the mileage pay rate and the payment method affect the probability of an accident or a logging violation. Moreover, they conclude the firm size matters, as large firms (1,000 to 4,999 employees) outperform the small firms (25 or fewer employees) with lower the probabilities of being involved in an accident, having a moving violation, and violating a logbook (Kristen Monaco and Emily Williams, 2000).

Belzer, Rodriguez, and Sedo examine the relationship between the various compensation practices of motor carriers and the resulting behavior. For their firm-level negative binomial regression, they gather data from four sources: The National Survey of Driver Wages (NSDW or Signpost), the National Motor Carrier Directory, the Motor Carrier Management Information System (MCMIS), and the UMTIP mentioned above to do three layers of the analysis. In the first study, they use the negative binomial with a combined dataset of NSDW and MCMIC, find that pay raise is significant at the 10% level, and the inverse relationship between compensation and crashes are almost unit elastic. In addition, for their individual level study at a firm, they use the J.B. Hunt data (11,540 individuals and 92,528 observations), which covers 26 months (Sep 1995- Sep 1996 and Mar 1997 - Feb 1998) before and after a major wage increase. This study shows that the pay elasticity of crashes is about -4. Since the elasticity varies across different model specifications, they estimate that the elasticity is better than -2. Moreover, they test a subsample of all employee drivers who are paid by miles in the UMTIP data set and find that a 10% increase in the mileage rate will reduce the probability of a crash by 21%. All three models show that driver pay is a strong predictor of driver safety. Besides, they use the UMTIP data to derive the backward bending labor supply curve (Michael H. Belzer et al., 2002). Their report sets the foundation on driver compensation and safety for all future studies, including the current one. One of the main contributions of the current study is to validate the relationship between compensation and safety again by using the latest MCMIS data and different statistical models.

Belzer and Sedo took an in-depth and analytical look at the long-haul truck drivers' attitude toward compensation, using UMTIP data. They use the efficiency wage theory, target earning hypothesis, and labor-leisure-tradeoff model to derive and visualize the backward bending supply curve, which estimates the labor-leisure tradeoff for long-distance truck drivers (and hence the labor-market for truck drivers) and suggests a typical driver's preference for mileage pay rate and labor supply. More specifically, they find the income effect starts dominating the substitution effect at the tipping point when the representative driver receives an average of 30.75 cents per mile in 1997 dollars (46 cents per mile in 2017 dollars) for working 69.77 hours per week. Although 69.77 hours per week seems well beyond the legal limit of 60 hours (Michael H. Belzer and Stanley A. Sedo, 2018), it is also consistent with Viscelli's findings in his book *The Big Rig: Trucking and the Decline of the American Dream* that drivers have strong incentives to dodge the HOS mandatory 60-hour rule by using different "logbook techniques" (Steve Viscelli, 2016).

In 2019, Kudo and Belzer use the 2010 NIOSH data set and find that higher mileage pay rates and employment-based health insurance significantly decrease the probability of moving violations. NIOSH data were collected during personal interviews with 1,265 long-haul truck drivers at 32 different truck stops across the 48 contiguous United States in 2010, in which questions were on truck driving history, work practices, driving environment, fatigue, sleep, injury history, health and medical conditions, and demographics (Guang X. Chen et al., 2015). It is similar to the UMTIP survey in 1997 but gives an updated view of the driver's portrait in 2010. In the current study, the primary data source is the most recent Motor Carrier Management Information System (MCMIS) data set, in which the data mainly comes from field offices through SAFETYNET, Compliance Analysis and Performance Review Information (CAPRI), and other sources. The monthly release includes four key datasets: Census, Inspection, Violation, and Crash for both interstate and intrastate carriers. Unlike all previous datasets mentioned above, which are either proprietary (J.B. Hunt) or cross-sectional (UMTIP and NIOSH), this MCMIS one is free to the public and provides a longitudinal view since it gets updated by FMCSA every month. All crash, violation, and inspection data are at the incident level, which provides much more granular information. Besides, few have fully utilized this MCMIS dataset for empirical studies.

In sum, a few scholars have tested the linkage between compensation and safety in the past two decades; results are consistent using different data sets. The results show that compensation is a strong predictor of crashes, suggesting if the compensation is low, then the probability of a crash or number of crashes (depending on the model) will be relatively high.

Motivation

Based on the past literature, the relationship between compensation and safety seems strong across all models in the literature. However, the implicit assumption is the decrease in compensation due to deregulation in the trucking industry pushes drivers to work more, which could cause more HOS violations, then eventually turns into crashes. From an enforcer's perspective, it is meaningful to know whether or issuing HOS violations and sending warning letters can reduce crashes. Meanwhile, the data sets used in the previous studies are at least 10-20 years old, in which the market dynamic could have changed materially. Therefore, the motivation for the current study is to test the relationship between HOS violations and crashes and validate the relationship between compensation and crashes, using different statistical approaches and updated datasets.

Furthermore, for each crash, the economic cost to society is enormous. According to the most recent studies by Harmon, Bahar, and Gross, the comprehensive crash unit cost with a fatality is about $11.3 million, while the crash per unit with different degree of injuries has a range from $655,000 to $125,600 in 2010 dollars on the national level (Tim Harmon et al., 2018).

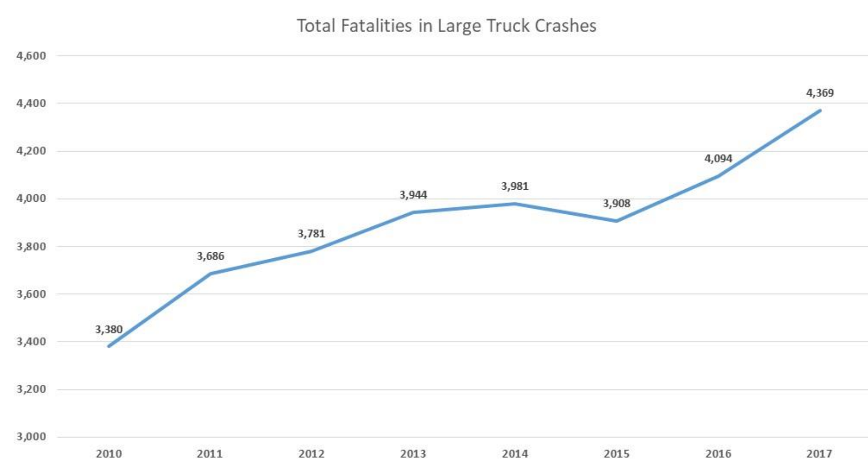


Figure 0.1 Historical Trend of Fatalities

Figure I.2.1 shows historical trend of fatalities in large truck crashes from 2010 to 2017 in the United States. By observation, the trend kept climbing over the past decade.

If we multiply the crashes with the per-unit cost, then the total economic cost is tremendous. If we can provide the regulator a better statistical tool to capture risky carriers, then the enforcement will be more precise and efficient, resulting in fewer crashes and lower economic costs. Therefore, our second motivation of the current study is to provide the FMCSA with a more comprehensive view of carriers' probabilities, a statistical method to quantify the riskiness of the carriers.

Overview

The dissertation will include three Chapters, all related to FMCSA violations, compensation, and safety.

In Chapter 2 hour of service (HOS) Compliance Violations and Crashes, we explore the linkage and causality between crashes and HOS violations for the intrastate property-carrying sector, using the MCMIS dataset for 2018. This is also answering the National Academy of Science, Engineering, Medicine's call for more analysis in this area. According to the estimated results, the sign of HOS violations on crashes is positive and statistically significant at the 1% level, suggesting more HOS violations correlates to more crashes. However, according to our Vector Autoregressive model (VAR), the favorable impact on reducing the total number of crashes lasts about eight months, while the peak of reduction happens in the first two months. Moreover, the hourly wage as a proxy for drivers' earnings indicates a persistent and favorable impact on lowering crashes, and this finding is aligned with results in recent studies. However, the current study is restricted to cross-sectional analysis in 2018, in which we assume intrastate carriers are homogeneous due to high market competition. In the next chapter, we will expand our sample period back to 2015 and take a longitudinal approach to validate the current findings further.

In Chapter 3 Compensation and Safety – A Longitudinal Study, we test the relationship between BASICs, compensation, and crashes; we validate the relationship between compensation and safety, implementing longitudinal analysis for a sample period from 2015 to 2018. The estimated results show that compensation is the most consistent and significant influencer of crashes, while the higher than the market average compensation makes a difference in our subgroup analysis since drivers become less sensitive to the difference in hourly wage. Based on our estimated elasticities, at the mean, 1% higher in hourly pay rate correlates to 1.8% fewer crashes over the sample period from 2015 to 2018, which will lead to a more considerable reduction in crashes for mid pay carriers since their elasticity is higher than high pay carriers. In other words, it is more cost-effective for mid pay group to offer a compensation raise.

Overall we think this suggests that though FMCSA should keep their current enforcement strategy (enforce on the BASICS while targeting the carriers they think are unsafe), they could obtain the strongest safety outcome by tracking driver pay (as the 2017 NAS report recommends) and take carrier pay into effect in their evaluation of safety effectiveness (Panel on the Review of the Compliance Safety and Accountability et al., 2017).

In Chapter 4 Safety Measurement and Economic Impact, we use the public data and an innovative bottom-up approach to estimate the intra-state property carrier's marginal probability of crashes. More specifically, we build a combined dataset from the BASIC violations, the OES wage, and the MCMIS crashes in 2017. Then, we run a logistic regression to get significant parameters for predicting the log(odds) of a crash, in which Hourly wage is a proxy for compensation, showing a strong power of prediction: the higher the wage rates, the lower the odds. Using linear transformation, we calculate the probability of a crash at the individual vehicle level in 2018, and then aggregate the individual probability of a crash to a joint one at the firm level for each intrastate carrier in our sample. Since the crashes data in 2018 are known in our full dataset, we can compare our estimated results to actual one. Pearson's correlation coefficient shows a value of 0.58, which is also statistically significant at the 1% level, suggesting a strong positive linear relationship between our estimated crashes and the actual ones.

Since the FMCSA's crash indicator is not available to the public, we simulate the FMCSA's crash indicator according to the FMCSA's methodology and find our proposed approach exhibits a 61% higher linear correlation than the FMCSA's. Consequently, we recommend FMCSA to use our proposed statistical method as a complement to the existing tools.

CHAPTER 2 HOS COMPLIANCE VIOLATIONS AND CRASHES

Introduction

The Panel on Research Methodologies and Statistical Approaches to Understanding Driver Fatigue Factors in Motor Carrier Safety, and Driver Health discussed the urgency of determining the causality between fatigue and crashes. They conclude that HOS regulations need to take into account the trade-off between the economic advantages of faster transportation and the disadvantages of an increasing number of crashes (Panel on Research Methodologies and Statistical Approaches to Understanding Driver Fatigue Factors in Motor Carrier Safety and Driver Health, Committee on National Statistics et al., 2016: 125)

This chapter aims to make this trade-off more explicit by linking increases in crash risk to increases in the number of FMCSA HOS compliance violations, using the MCMIS dataset for 2018.

Theory and Hypothesis

Deregulation in 1980 led to an increasingly competitive environment. In the past two decades, only a few studies have focused on compensation and safety in the trucking industry.

Kristen Monaco and Emily Williams (2000) use data from the 1997 Survey of 573 truck drivers conducted by the University of Michigan and estimate the probability of being involved in an accident, having a moving violation, or violating a logbook. They find that higher effective mileage rates were significantly associated with a lower probability of an accident and false logging. Dale Belman, Kristen A. Monaco and Taggert J. Brooks (2005) summarize these cross-sectional data and describes a portrait of truck driver's work in the book *Sailors of the Concrete Sea*.

Michael H. Belzer, Daniel A. Rodriguez and Stanley A. Sedo (2002) study the relationship between the various compensation practices of motor carriers and the resulting behavior, implementing a cross-sectional analysis of 102 nonunion TL carriers. According to their estimated results, each 10% higher in compensation correlates to a 9.2% lower crash rate, while including all components of compensation. Daniel A. Rodriguez et al. (2006) use a proprietary driver-level dataset from J.B. Hunt. Using survival analysis, they find that a 1% higher in pay rate leads to a 1.33% lower probability of a crash .

Michael H. Belzer and Stanley A. Sedo (2018) take an in-depth and analytical look at the long-haul truck drivers' attitude toward compensation. Based on the efficiency wage theory, target earning hypothesis, and labor-leisure model, they derived and visualized a backward bending supply curve, which describes a typical driver's preference for mileage pay rate and labor supply. More specifically, they find the income effect starts dominating the substitution effect at the tipping point when the representative driver receives an average of 30.75 cents per mile in 1997 dollars (46 cents per mile in 1977) for working 69.77 hours per week. Although 69.77 hours per week seems well beyond the legal limit of 60 hours, it is consistent with Steve Viscelli (2016)'s finding that drivers have strong incentives to dodge the HOS mandatory 60-hour rule by using different "logbook techniques," on page 61-64. Michael R. Faulkiner and Michael H. Belzer (2019) use J.B

Hunt data, which includes 87,887 monthly driver observations with 11,457 unique drivers. The dataset also includes driver demographics and operational characteristics. Using a Cox proportional hazards model, they find that substantially higher wages effectively improved driver retention rates, reducing turnover as well as the probability of a crash. These translate to cost savings and thus improves the firm's financial performance.

Takahiko Kudo and Michael H. Belzer (2019) use the 2010 NIOSH dataset and find that higher mileage pay rates and employment-based health insurance significantly decrease the probability of moving violations – a proxy for safety. Crashes were not used as the dependent variable because, during the survey, drivers were asked to report life-time crashes instead of the total number of crashes in a period.

However, in the recent literature, a few have tested the second part in the chain, just assuming the second theory holds. We tested whether or not the HOS related violations lead to crashes in the intra-state property carrier in Chapter 2.

The pay incentive approach makes sense because the efficiency wage theory suggests that employers need to pay higher than the market equilibrium compensation to prevent workers from shifting firms and to induce labor productivity. It also suggests that drivers believe that higher pay creates an incentive to drive safely in order to retain their jobs and improve their employability for future truck driving jobs (George A Akerlof and Janet L Yellen, 1990).

The classic labor and leisure model tells us the tradeoff between income and rest. In the case of the trucking industry. If most drivers are sensitive to earnings and have a target income higher than the market-clearing price, then they have a strong incentive to drive more, dodging the HOS regulations, which ultimately results in more crashes. In other words, the mismatch between their target earnings and their relatively low pay rate will give them an incentive to work more hours than is legally or safely allowable. (Michael H. Belzer and Stanley A. Sedo, 2018)

The hypothesis we are testing in this chapter is whether or not the HOS compliance violations lead to crashes for intrastate property carriers. If the estimated result is statistically significant, we then test whether the impact is transitory or permanent. Furthermore, we will validate the relationship between compensation and crashes, since the recent studies show a significant impact.

Data and Variables

The mission of the Federal Motor Carrier Safety Administration (FMCSA) is to prevent commercial motor vehicle (CMV) related injuries and fatalities. Currently, the Safety Measurement System (SMS) is the primary tool used to detect motor carriers with safety compliance issues. SMS includes 899 possible violations that may arise from roadside inspections and puts them into six Behavior Analysis and Safety Improvement Categories (BASICs): Unsafe Driving, Hours-of-Service Compliance, Vehicle Maintenance, Controlled Substances/Alcohol, Hazardous Materials Compliance, and Driver Fitness.

In the current study, our primary data source is the Motor Carrier Management Information System (MCMIS) dataset, merged across multiple years, as updated and released monthly by the Federal Motor Carrier Safety Administration (FMCSA). The data mainly come from field offices through SAFETYNET [1], Compliance Analysis and Performance Review Information (CAPRI), and other sources. The monthly release includes four key datasets: Census, Inspection, Violation, and Crash for both interstate and intrastate carriers. Because all Census data are at the firm level and carriers often update once a year or two, we choose to do our analysis at the firm level using annualized numbers.

Table II.3.1 Unique carrier observations

Year/Carrier Type	A	B	C	Grand Total
2015	49,508	**2,078**	**30,219**	81,805
2016	150,966	**3,552**	**30,937**	185,455
2017	265,282	**5,361**	**57,231**	327,874
2018	353,759	**6,785**	**84,139**	444,683
OBS	**819,515**	**17,776**	**202,526**	**1,039,817**

The Census dataset includes information on 1.04 million Interstate, Intrastate Hazmat, and Intrastate Non-Hazmat Motor Carriers. Table II.3.1 lists the distribution of observations across different types of carriers. FMCSA defines interstate carriers as Type A, intrastate hazmat carriers as Type B, and intrastate non-hazmat as Type C. In this chapter, our cross-sectional analysis will focus on intrastate carriers (Type B and C) in 2018, which add up to 90,924 observations. In addition to carrier operation type, the Census dataset also includes DOT number, passenger-carrier flag,

[1] SAFETYNET is a database management system that allows entry, access, analysis, and reporting of data from driver/vehicle inspections, crashes, compliance reviews, assignments, and complaints.

locations, MCS 150[2] update date, self-reported vehicle mileage traveled (VMT), the corresponding VMT year, number of power units, and number of drivers.

Locations in terms of states are referring to a carrier's physical location, the mailing location, and the location of the FMCSA state branch office that oversees the carrier. A typical interstate carrier operates in multiple states by definition, so it would be tough to distinguish the reported VMT by state or location. For example, if an interstate carrier's reported VMT in MCS150 is 100,000 miles, and the carrier's physical location is in California, we cannot assume that all miles are traveled within in CA, yet we cannot allocate the mileage across states given limited information in the MCMIS dataset. Therefore, the current study will focus on intrastate carriers. For intrastate carriers, those three locations must be the same, and the reported VMT means the mileage traveled in the carrier's operating state within the year. We believe this will add much precision to our estimation.

Moreover, we exclude all passenger carriers in this study because we want to focus on truck drivers, as transporting people is materially different from hauling commodities. Among all intrastate carriers who updated the MCS150 file in 2018, passenger carriers account for 2.2%, while property carriers account for the remaining 97.8%. However, as of July 2019, some intrastate carriers have not updated their VMT for 2018 yet. Because of this, we reduce the sample size to 15,789 unique intrastate property carriers, including hazmat and non-hazmat ones.

[2] MCS 150 is the file that every carrier uses to apply for the DOT number, and FCMSA requires carriers to update this file if there is any change in business such as legal name, address, and other data.

The Inspection dataset includes incident-level information regarding the different levels of BASIC related inspections, which are relevant to unsafe driving, Hours-of-Service compliance, driver fitness, and vehicle maintenance. Also, the dataset includes the DOT number, state, and date, which are used for mapping.

The Violation dataset includes five BASIC related violations. The unsafe driving violation refers to careless or reckless driving, such as speeding. Hours-of-Service (HOS) compliance violation is driving exceeding hours or false logging. Driver fitness violation is typically driving without a commercial driver's license (CDL) due to medical conditions. Controlled substances/alcohol violation means driving under the influence of alcohol or drugs. Vehicle maintenance violation is commonly causing by poor maintenance of the truck.

Table II.3.1 Top 10 HOS Compliance Violations

HOS Violation Codes	SECTION_DESC	% of total
3958	Record of Duty Status violation (general/form and manner)	9.56%
3953A2PR	Driving beyond 14 hour duty period	6.93%
3953A3PROP	Driving beyond 11 hour driving limit in a 14 hour period	6.34%
3953A2PROP	Driving beyond 14 hour duty period	6.20%
3953A3PR	Driving beyond 11 hour driving limit in a 14 hour period	5.68%
3953A3II	Driving beyond 8 hour limit since the end of the last off duty or sleeper period	5.35%
3958E	False report of drivers record of duty status	5.19%
3958F01	Drivers record of duty status not current	4.82%
39522H4	Driver failed to maintain supply of blank drivers records of duty status graph-grids	4.63%
3958A	No drivers record of duty status when one is required	4.54%
Subtotal		59.24%

Table II.3.2 shows the top 10 HOS compliance violations in 2018 by weight, which account for 59.24% of the total HOS violations. Although violation codes are slightly different due to the classification and the local interpretation, they all fall into two broader categories: driving beyond the daily limit of 11 hours or working beyond 14 hours and false logging, which could potentially serve the same purpose of driving more hours than legally allowed. According to the latest HOS regulation enacted in 2014, all property-carrying drivers cannot drive beyond 11 hours after 10 consecutive hours off duty, nor can they drive beyond 14 hours per day when taking non-driving on-duty hours into account. In other words, the daily maximum driving allowance is 11 hours, but the drivers can work up to 14 hours a day, including non-driving duties, then they are required to take a 10-hour break to be able to drive another 11 hours and work to a maximum of 14, while the weekly cap of work is 60 hours for 7 consecutive days and 70 hours for 8 consecutive days. After that, they must take a 34-hour break to reset the clock or wait until they pick up hours after their eighth day. In theory, if a driver works 14 hours on Sunday and takes a 34-hour break from Sunday to Monday, starts a new round on Tuesday and works 14 hours a day from Tuesday to Sunday, that will add up to 84 hours in 8 consecutive days. (Gregory M. Saltzman and Michael H. Belzer, 2007) According to Michael H. Belzer and Stanley A. Sedo (2018), who also used the UMTIP survey data, a typical long haul employee truck driver worked 69.77 hours per week in 1997.

The Crash dataset includes incident-level data such as fatalities, injuries, light conditions, and weather conditions. Also, the dataset has the DOT number, state, and date, which are used for mapping in this study.

In addition to these four datasets from MCMIS, we get the wage dataset from the Occupational Employment Statistics (OES) Survey by state and occupation, and the population data from the U.S. Census Bureau. OES provides an update on the median wage of each occupation in the US in May each year, which also includes a wide range of classification for a single industry. In this study, it is most relevant to look at truck transportation (NAICS 484000), and we narrow down to “Heavy and Tractor-Trailer Truck Drivers” (OCC 53-3032). Furthermore, we choose the median hourly pay of each state as our wage variable since we believe the wage of intrastate carriers will not be materially different from each other due to competition and high turnover in the market, while the hourly rates may differ across states due to the cost of living. Also, we include state population density per square mile in 2015 as a control variable and a proxy for state characteristics, and we get estimates from the United States Census Bureau.

Table II.4.1 Descriptive Statistics

Summary statistics						
Variable	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**	**Label**
CRASHES	14957	0.20	1.39	0	107	Number of crashes
HOS	14957	0.07	0.62	0	38	Number of HOS compliance violations
UNSAFE	14957	0.11	0.58	0	13	Number of unsafe driving violations
DR_FIT	14957	0.12	0.68	0	26	Numebr of driver fitness violations
SUBT	14957	0.00	0.07	0	5	Number of controlled subtances violations
VM	14957	2.01	6.09	0	131	Number of vehicle maintenance violations
WAGE	14957	20.14	1.50	17.14	25.67	Median hourly wage in the carrier's state
Pop_density_m2	14957	224.68	290.72	1	11011	Population density in 2015
VMT	14957	316,005	18,263,635	1,000	2,174,200,000	Reported VMT
HM_FLAG2	14957	0.02	0.13	0	1	Hazmart flag

Table II.4.1 shows the descriptive statistics of variables. The number of observations reduced to 14,975 because some firms have not done their MC 150 filing for 2018, and we exclude the carriers with the dual status of interstate and intrastate carriers since the goal of the study is to focus on the intrastate carriers. Also, there were quite a few duplicates in the raw dataset. Also, we restricted our sample to 50 states. All basic violations are the count of occurrence at the firm level, and we standardize the measure by dividing the by the number of power units in 2018.

In addition to the BASICs, we believe it is essential to add earnings to the model, as recent studies have found statistical evidence that higher pay incentives correlates to fewer crashes or lower the probability of a crash (Michael H. Belzer, Daniel A. Rodriguez and Stanley A. Sedo, 2002, Michael R. Faulkiner and Michael H. Belzer, 2019, Takahiko Kudo and Michael H. Belzer, 2019, Daniel A. Rodriguez, Felipe Targa and Michael H. Belzer, 2006).

For an intrastate property carrier in 2018, the hourly wage has a mean of \$20.14 with a standard deviation of \$1.50, a low of \$17.14, and a high of \$25.67. As of Dec 2018, the average hourly earnings in the US is \$27.53 in 2018 dollars, according to the U.S. Bureau of Labor Statistics [3]. As long as the income has not reached the driver's target level, the slope of the labor supply curve remains positive (Michael H. Belzer and Stanley A. Sedo, 2018). In other words, the truck driver will choose to work more.

In addition, drivers are willing to commit small violations, which eventually adds up to crashes (Steve Viscelli, 2016). Therefore, we believe drivers have an incentive to drive more to pursue higher income and take the risk of violating HOS regulations in our sample period. Based on the descriptive statistics shown above, on average, an intrastate carrier had a 0.20 crash (less than one crash) in 2018. The

[3] U.S. Bureau of Labor Statistics, Average Hourly Earnings of All Employees: Total Private [CES0500000003], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CES0500000003, August 27, 2019.

count of crashes is purely based on distinct incident IDs, so there is a minimum double-counting issue in the current study. Since these are all local police-reported crashes, the total number of crashes is likely understated, but on the other hand, those unreported crashes are presumably less severe than the reported ones. A reportable crash means a crash involving at least one fatality, one injury requiring transportation to a medical facility, or one vehicle towed from the scene. Moreover, each BASIC violation represents the number of violations that an intrastate carrier had in 2018.

HOS compliance violations have a mean of 0.07, and a standard deviation of 0.62, meaning 90% of the intrastate motor carriers had fewer than 2 crashes. Unsafe driving violations have a mean of 0.11 and a standard deviation of 0.58, meaning 90% of the intrastate carriers had less than 2 violations, while for a single carrier, the maximum number of violations per vehicle can be as high as 13. In comparison to other BASICs, the unsafe driving violations have the second-highest total number. Driver fitness violations have a mean of 0.12, and a standard deviation of 0.68, meaning 90% of the intrastate had fewer than 2 violations, while for a single carrier, the maximum number of violations per vehicle can be as high as 26.

Controlled substances/alcohol violations have a mean close to 0 and a standard deviation of 0.07, meaning 99% of the intrastate had less than 1 violation, while for a single carrier, the maximum number of violations per vehicle can be as high as 5. This is the least common violation in the sample with a low mean and standard deviation.

Vehicle maintenance violations have a mean of 2.01, and a standard deviation of 6.09, while for a single carrier, the maximum number of violations per vehicle can be as high as 131.

On average, an intrastate property-carrier has 4.33 power units with a standard deviation of 18.95. This is consistent with the statistics of vehicle maintenance violations and suggests most carriers are small ones with 5 or fewer trucks while there are a few giants in the industry, which drives the standard deviation up, as the maximum shows 1,273 power units. In the census dataset, the number of drivers is also included. However, a high correlation exists between drivers and trucks, and we choose the latter one to avoid the multicollinearity issue. As Table II.4.2 shows below, the correlation coefficient between power units and driver total is 0.88, suggesting a nearly 1:1 relationship between trucks and drivers; this suggests that most trucks are driven by one driver. Meanwhile, other correlations are relatively low, resolving our concern about multicollinearity.

Table II.2.2 Correlation Coefficient Matrix

Pearson Correlation Coefficients, N = 14957									
	HOS	**UNSAFE**	**DR_FIT**	**SUBT**	**VM**	**lwage**	**lPop_density_m2**	**LVMT**	**HM_FLAG2**
HOS	1.00								
UNSAFE	0.15	1.00							
DR_FIT	0.12	0.16	1.00						
SUBT	0.07	0.01	0.05	1.00					
VM	0.24	0.20	0.27	0.06	1.00				
lwage	-0.03	-0.03	0.00	-0.01	-0.09	1.00			
lPop_density_m2	0.01	0.03	0.05	0.00	0.02	-0.06	1.00		
LVMT	0.03	0.05	0.01	0.02	0.08	-0.09	0.04	1.00	
HM_FLAG2	-0.01	0.00	-0.01	0.02	-0.01	-0.03	0.01	0.10	1.00

State population density per square mile has a mean of 225 people per square mile and a high of 11,011 persons per square mile in 2015. Reported vehicle mileage traveled has a mean of 316,005 per carrier in 2018. The HM flag is an indicator for differentiating hazmat and non-hazmat carriers– 1 for hazmat and 0 otherwise. Hourly wage is in log transformation because we want to estimate the elasticity. Reported VMT and State population density per square mile are in natural logarithm because that helps to minimize the excessive impact of large numbers.

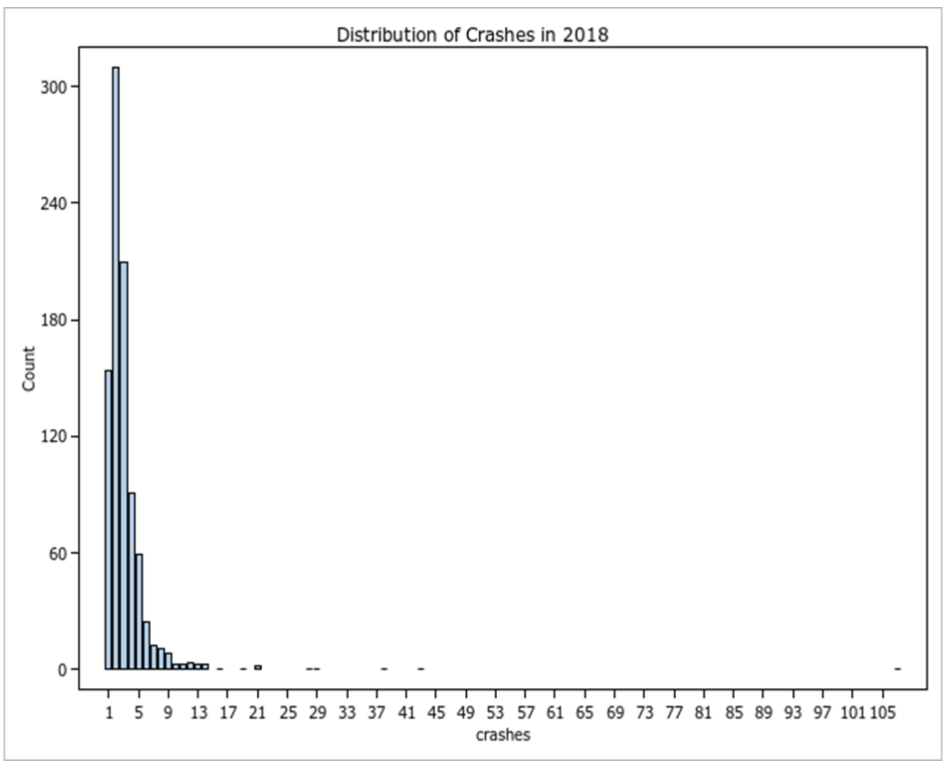
To sum up, our independents are 5 BASIC violations and hourly pay, while the other three are control variables. However, we want to bring the concern that a systematic sampling bias may exist, which drives the mean value up because inspection data on which BASICS are based comes mostly from roadside inspections that are biased. Enforcement people may form their own perception of target carriers, trucks, and drivers that they think are likely to be in violation. Therefore, the fundamental data collection process is biased, and it completely violates the random selection requirement of most statistics, affects all BASIC violations, while crashes and OES wages are more deterministic, as they are more explicit.

Regression Analysis

Takahiko Kudo and Michael H. Belzer (2019) explore the 2010 NIOSH dataset and their estimated results suggest that the mileage pay rate (a ratio of total annual earnings to the number of miles driven) and employment-based health insurance significantly decrease the probability of moving violations, in which the moving violations are used as a proxy for safety performance. The number of crashes in the NIOSH survey is questionable since because the surveyors asked drivers how many crashes they have experienced during their careers instead of during a specified period (such as the previous year), while they asked drivers to report compensation over the past year. They also do not explore the causality between moving violations and crashes because of the cross-sectional nature of the survey data. In this paper, in contrast, we explore this causality in the intrastate property-carrying sector of the trucking industry in 2018 using MCMIS firm-level data.

All variables are mapped with a constraint on the year so that they are more aligned with each other than the NIOSH one. Indeed, while each firm is unique, in this chapter, we want to test our hypothesis that moving violations lead to crashes from a typical firm's perspective. In later chapters, we will examine the firm's characteristics.

Figure II.5.1 Distribution of Crashes in 2018



From Figure II.5.1 above, we notice the distribution of crashes is not normal, so using OLS leads to biased results. Instead, we use Poisson regression as the baseline model and negative binomial regression model as our preferred model; both can be written as:

$$
\begin{aligned}
&Log(Crashes) \\
&\qquad = \beta_0 + \beta_1\, HOS\, Viol + \beta_2\, Unsafe\ driving\ Viol \\
&\qquad + \beta_3\, Driver\ fitness\ Viol + \beta_4\, Substance\ alcohol\ Viol \\
&\qquad + \beta_5\, Vehicle\ maintenance\ Viol + \beta_6\, Log(Hourly\ wage \\
&\qquad + \beta_7\, Log\ (Population\ density) + \beta_8\, Hazmat\ Flag \\
&\qquad + \beta_9\, Log\ (VMT)
\end{aligned}
$$

Estimated Results

Table II.6.1 - Dependent variable – Log(Crashes)

	Poisson		NB - preferred	
Variable	**Parameter Estimate**	**Pr > |t|**	**Parameter Estimate**	**Pr > |t|**
Intercept	-0.02	0.98	0.30	0.88
HOS	**0.09**	<.0001	**0.25**	0.01
UNSAFE	0.04	0.11	0.22	0.01
DR_FIT	0.03	0.18	0.02	0.75
SUBT	0.12	0.26	0.33	0.63
VM	0.01	<.0001	0.04	<.0001
lwage	**-3.09**	<.0001	**-3.16**	<.0001
lPop_density_m2	0.13	<.0001	0.19	<.0001
LVMT	0.61	<.0001	0.56	<.0001
HM_FLAG2	0.97	<.0001	0.77	0.01
Dispersion	1		17.37	
Log Likelihood	-5199.2		-2088.4	
Full Log Likelihood	-8115.6		-5004.9	
AIC (smaller is better)	16251.2		10031.8	

From the estimated results above, three BASICS are statistically significant at the 1% level in our preferred model, with 14,947 observations. Driver fitness and controlled substances are not statistically significant at the 10% level, which is consistent with the findings in the NAS panel 2017. Hourly wage exhibits strong and consistent impact across two models. The negative binomial model is preferred to the Poisson one because the overdispersion parameter is greater than 1 which means the usage of negative binomial model is justified, and both loglikelihood and AIC exhibit better goodness of fit in the NB than those for Poisson,

The HOS violation is statistically significant at the 1% level, and the sign of parameter is consistent with our prior expectations. The estimated result means 1 more count of the marginal increase in HOS violation per power unit correlates to 0.09 increase in log count of crashes, which translates to 1.09 crashes[4]. Intuitively, we would think, and FMCSA believes that HOS related violations such as driving over the time limit lead to fatigue and stress, and thus increase the probability of crashes. However, the data come from regulatory enforcement, not from a random sample of the population. Further, the enforcement community targets trucking companies and trucks that it suspects of operating dangerously on any of these dimensions. Because enforcement is not random, and BASICS violations are found in a targeted way, violations are systematically higher than they would be in the general population. In addition, this analysis is at the firm level, so the estimated result suggests the typical intrastate property carrier reacts to the HOS violations on an annual basis.

The estimated parameter of the unsafe driving violation has a positive sign, and it is statistically significant at the 1% level, which is consistent with our expectations. This

[4] Log(crashes)=0.09, crashes = exp(0.09) = 1.09.

violation is behavior-related and heavily relies on the driver's driving habits; some drivers like speeding or following too closely, and they have been doing this for years, so eventually, it just a matter of being caught or causing a crash.

The estimated parameter of driver fitness has a positive sign, but it is not statistically significant at the 10% level. One of the most common violations in this category is driving without a commercial driver's license (CDL) due to inadequate medical conditions. Once caught, the driver can no longer drive, so it decreases the probability of future crashes in general at the carrier level. Besides, the drivers are more aware of their medical conditions if they cannot renew the CDL, which implies the condition is severe so that they may drive less in exchange for health willingly or unwillingly. On the other hand, the existing medical condition may physically prevent them from driving more. Therefore, the net impact can be ambiguous, and the estimated parameter may be systematically true among intrastate carriers in 2018. This is consistent with the findings in the NAS 2017 Panel.

The estimated parameter of the controlled substances and drug violation has a positive sign, but the estimated parameter is not statistically significant at the 10% level. We expect a positive relationship between controlled substances and crashes. However, the currently estimated result shows that controlled substances are not predictive of crashes for intrastate carriers in 2018, which is consistent with the findings in the NAS 2017 panel.

The estimated parameter of vehicle maintenance has a positive sign, and the estimated parameter is statistically significant at the 1% level, which is aligned with our expectations. The marginal magnitude of each incremental maintenance violation does add risks of crashes.

The sign of log (hourly pay) is negative and statistically significant at the 1% level. This estimation is consistent with our expectation and aligned with findings in the current literature; experienced drivers will react to the pay increase and drive more safely as the opportunity cost of crashes increases, and the actual income gets closer to their target level. (Michael H. Belzer, Daniel A. Rodriguez and Stanley A. Sedo, 2002, Michael H. Belzer and Stanley A. Sedo, 2018, Michael R. Faulkiner and Michael H. Belzer, 2019, Takahiko Kudo and Michael H. Belzer, 2019, Kristen Monaco and Emily Williams, 2000, Daniel A. Rodriguez, Felipe Targa and Michael H. Belzer, 2006). Since we take the log of hourly wages, the parameter can be interpreted as the elasticity in this model, which is -3.16. That shows the drivers' reaction to change in wage on crashes is elastic, and 1% higher hour wages correspond to 3.16% fewer crashes, holding other things the same.

The state population density is another control variable which aims to capture some state-level characteristics. The estimated parameter is statistically significant at the 1% level, suggesting a crash is more likely to happen in California than in Alaska, given a more condensed population. We expect more people means more cars and traffic in the US, which would increase the likelihood of crashes, regardless of the carrier's role in the crash.

The estimated parameter of vehicle mileage traveled has a positive sign, and it is statistically significant at the 1% level. Since we are focusing on intrastate carriers, the reported VMT by each carrier represents mileage traveled within the state of operation. The current results also confirm the more mileage driven, the more crashes may occur, which is consistent with our expectation.

The estimated parameter of the hazmat flag has a positive sign, and it is statistically significant at the 1% level, which indicates the current FMCSA classification of the hazmat and non-hazmat matters. The estimated results suggest that an intrastate hazmat carrier will have more crashes than a non-hazmat one. This is contrary to our expectations because usually, hazmat drivers receive more training before hitting the road.

Discussion on HOS Compliance Violations

In the previous section, we discussed the currently estimated results and explored the causality between fatigued violations and crashes for a common intrastate property carrier. Because the sign of the parameter is opposite to what we expected, we decide to test further whether the currently favorable impact is transitory or permanent. In other words, we have explored the relationship using a cross-sectional method, and now we want to test it in a time-series way, using a Vector Autoregressive Model (VAR).

We use the VAR model because it is a stochastic model used to capture the linear inter-dependencies via time series analysis, which does not require any specific classification of endogenous and exogenous variables as structural models do. Besides, we believe reverse causality may exist between crashes and HOS violations, and the VAR model can easily handle such feedback without an instrumental variable.

More importantly, the forecasted impulse response graphs help to explain and predict the inter-response of one standard shock, using the historical data.

Time Series Analysis of HOS Violation

For this time-series discussion, we treated intrastate property carriers as a whole since we want to prescribe the outcomes from an average firm's perspective, such that the interpretation of the estimated result will be comparable to the OLS one.

The sample period for this time series analysis is from Jan2014 to Mar2019, using monthly aggregation data for all intrastate property carriers in the MCMIS dataset. Endogenous variables are the total crashes of the month, the total HOS inspections of the month, and the total HOS violations of the month. The US monthly unemployment rate serves as a control variable and a proxy for the economic environment at that point in time. For stationarity reasons, the unemployment rate has been changed to the first-order difference form since it is an I(1) variable[5]. All other variables are in the level form since they are I(0) variables.

Table II.7.1 - Lag selection

Sample: 2014M01 2019M03
Included observations: 58

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2063.556	NA	1.08e+26	71.29502	71.43712	71.35037
1	-1928.172	247.4250	1.76e+24*	67.17835*	67.88885*	67.45510*

[5] I(1) means the first order of integration, an I(1) variable will be stationary after taking the first difference.

2	-1914.568	22.98661	1.93e+24	67.26096	68.53986	67.75912
3	-1901.848	19.73765	2.21e+24	67.37407	69.22136	68.09363
4	-1887.124	20.81685	2.40e+24	67.41807	69.83376	68.35903
5	-1864.829	28.44555*	2.06e+24	67.20099	70.18508	68.36335

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table II.7.2 - Stationarity Test

Roots of Characteristic Polynomial	
Root	Modulus
0.917017	0.917017
0.853960	0.853960
-0.317601	0.317601
0.122485	0.122485
No root lies outside the unit circle. VAR satisfies the stability condition.	

From Table II.7.1, both Akaike information criterion (AIC) and Schwarz information criterion (SIC) recommend the optimal lag to be 1, while the unit root test results in Table II.7.2 show that VAR satisfies the stability condition as no unit root lies outside the unit circle, we choose to use VAR(1) model for this discussion.

VAR(1) model:

Eq1:

$$Crash_t = \beta_0 + \beta_1 \ HOS\ violation_{t-1} + \beta_2 \ HOS\ Inspection_{t-1} + \beta_3 \ US\ unemployment\ rate_{t-1}$$

Eq2:

$$HOS\ Violation_t = \beta_4 + \beta_5 \ Crash_{t-1} + \beta_6 \ HOS\ Inspection_{t-1} + \beta_7 \ US\ unemployment\ rate_{t-1}$$

Eq3:

$$HOS\ Inspection_t = \beta_8 + \beta_9 \ HOS\ violation_{t-1} + \beta_{10} \ Crash_{t-1} + \beta_{11} \ US\ unemployment\ rate_{t-1}$$

where:

$Crash_t$ = the total number of intrastate property carrier-related crashes in month t

HOS_Vio_t = the total number of intrastate property carriers HOS violations in month t

HOS_Insp_t = the total number of intrastate property carriers HOS inspections in month t

US unemployment $rate_{t-1}$ = the US unemployment rate at month t-1, which is a control variable

Based on the VAR(1) structure, we expect that last month's number of HOS violations, inspections, and the economic environment will affect the number of crashes in the current month. Correspondingly, crashes happened in the last month, and the number of inspections will affect the number of HOS violations this month. And the number of crashes and violations that happened in the last month will affect the number of inspections this month. The monthly US unemployment rate is a proxy for the economic condition in the sample.

Impulse Response Figures

According to VAR(1) estimated results, we generated impulse response functions and visualized the outcomes as follow:

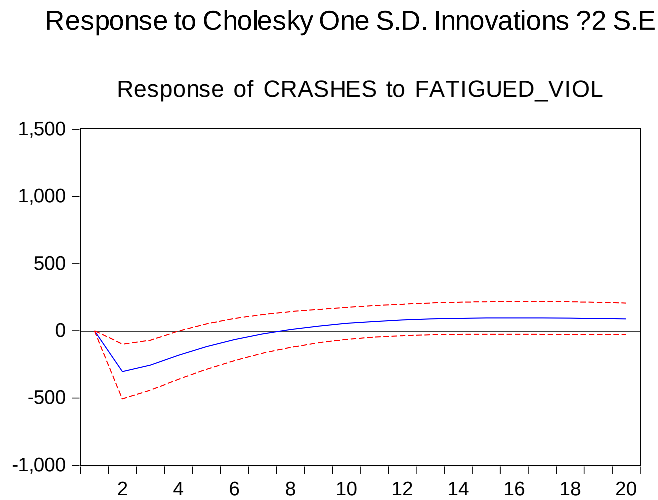


Figure II.7.1 Response of Crashes to HOS Violations

The figure above shows the response of crashes to one positive shock of HOS violations, which could come from enforcement action. The horizontal axis represents months after the shock, while the vertical axis reflects the marginal movements of the total number of crashes after the shock. The blue line shows the estimated response, and the red dash lines show the 95% confidence interval. The current results show that on average for an intrastate property carrier initially has a favorable response to HOS violations for the first 2 months. However, the mean response diminishes over the following 5 months and turns into unfavorable after the 7th month. This result is consistent with the OLS finding in section 4.5, where we see the parameter of HOS violation has a negative sign in our cross-sectional analysis on a yearly basis. However, the time-series analysis indicates the impact is transitory. From the policy perspective, we would recommend FMCSA to send follow up letters six to seven months after sending warning letters, in order to remind those carriers of the consequence of crashes. This would keep refreshing their minds, as long as the letters are accompanied by fresh inspections.

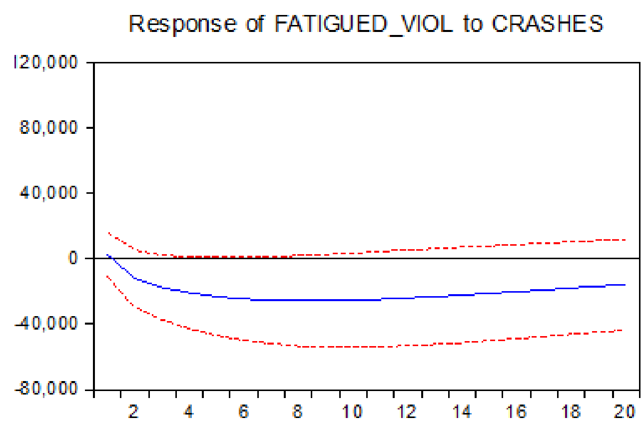


Figure II.7.2 Response of HOS Violations to Crashes

Figure II.7.2 shows the response of HOS violations to one shock of crashes. The horizontal axis represents months after the shock, while the vertical axis reflects the marginal movements of the total number of HOS violations after the shock. The blue line shows the estimated response, while the red dash lines show the 95% confidence interval. According to the figure, a typical intrastate carrier reacts to crashes, one standard shock of crashes will follow by reductions in the marginal number of HOS violations. The response lasts more than 20 months at a diminishing rate. Also, it suggests that reverse causality between crashes and HOS violations exists at the intrastate sector level, although this may not hold at the individual carrier level.

Consequently, in this discussion, we confirm that the OLS estimate of the favorable impact of HOS violations on crashes is statistically significant and influential for a typical intrastate property carrier. The impact will be more effective in the first two months, while the effectiveness declines over the following 4-6 months. On the other hand, the reverse causality exists, meaning that a typical intrastate carrier reacts to crashes as we see the estimated HOS violations drop over the next 20 months following a shock on crashes.

Conclusion

In this chapter, we explore the linkage and causality between crashes and HOS violations for the intrastate property-carrying sector, using the MCMIS dataset for 2018. This is also an answer to the National Academy of Science, Engineering, Medicine's call for more analysis in this area. According to the estimated results, the impact of HOS violations on crashes is positive, meaning more HOS violations correspond to more crashes on an annual basis. According to our VAR(1) model, in the short run an average interstate carrier reacts to HOS violations by taking some unobserved action that reduces crashes, as we see the crashes decrease after the shock. However, this favorable impact lasts about 8 months on average, while the peak of reduction happens in the first two months. Moreover, the hourly wage indicates a strong and favorable impact on crashes, and this finding is aligned with results in recent studies. The estimated elasticity is -3.16 in 2018 which shows that the pay incentive is a main driver of safety, proxied by fewer crashes. Therefore, FMCSA should consider adding this economic variable to the safety measurement system.

However, the current study is restricted to cross-sectional analysis in 2018, in which we assume intrastate carriers are homogeneous due to high market competition. In the next chapter, we will expand our sample period back to 2015 and take a longitudinal approach to further validate the current findings.

CHAPTER 3 COMPENSATION AND SAFETY – A LONGITUDINAL STUDY

Introduction

In the previous chapter, we explored the relationship between FMCSA violations and crashes. Using the 2018 cross-sectional analysis, we found that some FMCSA BASIC violations but not all have statistically significant impacts on the number of crashes, although most signs are contrary to our expectations. In addition, the hourly pay variable shows a favorable and statistically significant impact on crashes.

However, one of the assumptions we made is that all intra-state property carriers are the same due to high market competition, which may not be accurate, especially over time. Therefore, in this chapter, we release this constraint by implementing the random effect model with four years of observations using our combined MCMIS dataset.

Furthermore, we will revisit the impact of pay incentives on crash using the MCMIS data, validate the results based on the economic theories, and estimate marginal impacts in terms of elasticity.

Literature Review and Economic Theory

Literature Review

Deregulation in 1980 led to an increasingly competitive environment. In the past two decades, only a few studies have focused on compensation and safety in the trucking industry.

Kristen Monaco and Emily Williams (2000) use data from the 1997 Survey of 573 truck drivers conducted by the University of Michigan and estimate the probability of being involved in an accident, having a moving violation, or violating a logbook. They find that higher effective mileage rates were significantly associated with a lower probability of an accident and false logging. Dale Belman, Kristen A. Monaco and Taggert J. Brooks (2005) summarize these cross-sectional data and describes a portrait of truck driver's work in the book *Sailors of the Concrete Sea*.

Michael H. Belzer, Daniel A. Rodriguez and Stanley A. Sedo (2002) study the relationship between the various compensation practices of motor carriers and the resulting behavior, implementing a cross-sectional analysis of 102 nonunion TL carriers. According to their estimated results, every 10% higher compensation correlates to a 9.2% lower crash rate, while including all components of compensation. Daniel A. Rodriguez, Felipe Targa and Michael H. Belzer (2006) use a proprietary driver-level dataset from J.B. Hunt. Using survival analysis, they find that a 1% higher pay rate correlates to a 1.33% lower crash risk.

Michael H. Belzer and Stanley A. Sedo (2018) take an in-depth and analytical look at the long-haul truck drivers' attitude toward compensation. Based on the efficiency wage theory, target earning hypothesis, and labor-leisure model, they derived and visualized a backward bending supply curve, which describes a typical driver's preference for mileage pay rate and labor supply. More specifically, they find the income effect starts dominating the substitution effect at the tipping point when the representative driver receives an average of 30.75 cents per mile in 1997 dollars (46 cents per mile in 2017 dollars) for working 69.77 hours per week. Although 69.77 hours per week seems well beyond the legal limit of 60 hours, it is consistent with Steve Viscelli (2016)'s finding that drivers have strong incentives to dodge the HOS mandatory 60-hour rule by using different "logbook techniques" (Viscelli, 2016, page 61-64).

Michael R. Faulkiner and Michael H. Belzer (2019) use proprietary data provided by J.B hunt, which includes 87,887 monthly driver observations with 11,457 unique drivers. The dataset also includes driver demographics and operational characteristics. Using a Cox proportional hazards model, they find that a higher wage effectively improved driver retention rates, reducing turnover as well as the probability of a crash. These translate to cost savings and thus improves the firm's financial performance.

Takahiko Kudo and Michael H. Belzer (2019) use the 2010 NIOSH dataset and find that higher mileage pay rates and employment-based health insurance significantly decrease the probability of moving violations – a proxy for safety. Crashes were not used as the dependent variable because, during the survey, drivers were asked to report life-time crashes instead of the total number of crashes in a period. However, in the recent literature, few scholars have tested the second part in the chain, just assuming the second theory holds. We tested whether or not the HOS related violations lead to crashes in the intra-state property carrier in Chapter 2.

Economic Theories

MH Belzer et al. (2002) were the pioneers in testing the relationship between compensation and safety in the trucking industry and they provide the theoretical framework for future studies, such as (Michael H. Belzer and Stanley A. Sedo, 2018, Michael R. Faulkiner and Michael H. Belzer, 2019, Takahiko Kudo and Michael H. Belzer, 2019, Daniel A. Rodriguez, Felipe Targa and Michael H. Belzer, 2006, Gregory M. Saltzman and Michael H. Belzer, 2007). The current empirical studies will follow the existing framework of the efficiency wage hypothesis and the labor leisure model, which documents the backward bending labor supply curve to validate the linkage between compensation and safety. The statistical models will utilize the recent MCMIS dataset, which has not been done before.

Michael H. Belzer (2012) gives a comprehensive review of the literature and further characterizes the linkage between compensation and safety in the trucking industry. The classic definition of the efficiency wage is what a profit-maximizing firm offers to minimize the labor cost per efficiency unit, which also equates to the firm's marginal product. However, the efficiency wage hypothesis (Janet Yellen, 1984) suggests that in some markets, employers need to pay higher than the market equilibrium compensation to prevent workers from shifting firms and to induce labor productivity. From an employer's perspective, this action will attract high-quality workers and lower the turnover rate, because the worker cannot find an alternative in the market. In the context of the trucking industry, the hypothesis suggests that higher than the market-clearing wage can attract good drivers and thus improve safety performance. Michael R. Faulkiner and Michael H. Belzer (2019) show that the experienced drivers with high wages pay for themselves by bringing the employer positive net present value on the labor investment.

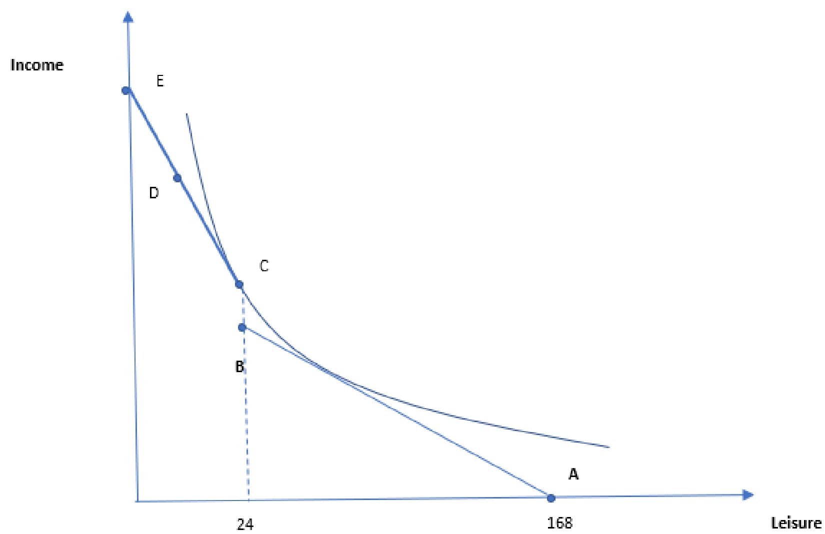
On the other hand, higher pay creates an incentive for truck drivers to drive safely in order to retain their currently higher than the market wage. Meanwhile, safely driving records to improve their employability for future truck driving jobs. Consequently, based on the efficiency wage hypothesis, we believe that a wage increase in the highly competitive trucking industry will improve a carrier's safety performance without sacrificing profitability.

The classic labor and leisure model show the tradeoff between income and leisure. In the trucking industry, the model is subject to the Hour-of-Service constraint, which at least conceptually is 60 hours per 7 consecutive days. If most drivers are sensitive to earnings and have a target income higher than the market-clearing price, then they have a strong incentive to drive more, ignore the HOS regulations, which ultimately results in crashes. In other words, the mismatch between their target earnings and their relatively low pay rate will give them an incentive to work more hours than is legally or safely allowable.

Figure III.2.1 shows that a truck driver can choose work hours from E-D-C because they are partially exempted from the Fair Labor Standards Act (FLSA), while a typical worker in the U.S. is subject to a practical constraint due to influence of premium pay aspect of A-B. C shows the situation where a driver is indifferent from a 40-hour FLSA covered worker, where D is the point that a driver can get a higher income by exceeding the HOS limit.

This model shows that drivers have economic reasons to keep on trucking due to the higher earnings. However, if they are not satisfied with the difference between B and C, they can still work more but at the cost of HOS violations, and trading off safety and health conditions (Michael H. Belzer and Stanley A. Sedo, 2018).

Figure III.2.1 Labor Leisure Model (Belzer and Sedo 2018)



Furthermore, based on the labor and leisure model, we define a driver's utility function as:

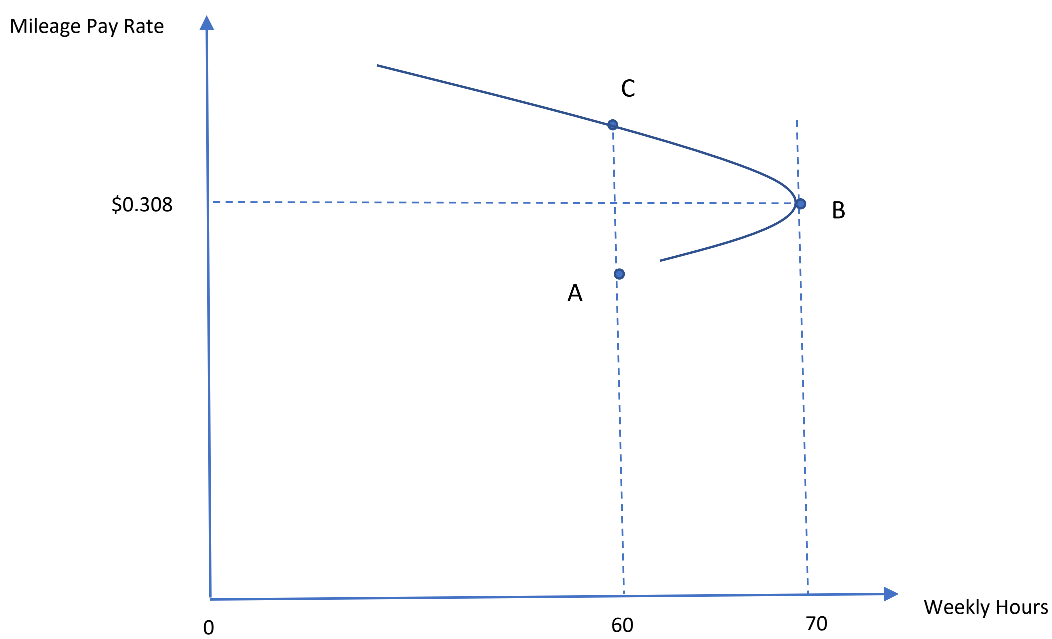
$$U = U(C, L)$$

$$\text{S.T.} \;\; C = wH + Y$$

$$T = H + L$$

Where U is a strictly quasi-concave and can be differentiated twice. C represents the total consumption of the driver. L is the hours of leisure, and H is the hours of work. T is the time constraint. w is the hourly wage rate, and Y is the driver's autonomous income. If we assume the marginal rate of substitution between C and L is diminishing or $\frac{\partial^2 U}{\partial C \partial L} < 0$, then maximizing driver's utility function subject to constraints, we can derive the labor supply function as $H = f(w, Y)$, where a change in hourly wages can be denoted as $\frac{\partial H}{\partial w}$. The net impact of a marginal change in w on H used to be ambiguous since both income effect and substitution effect will be presented. However, recent studies show that this can be demonstrated by a backward bending supply curve, as shown in figure III.2.2 below.

Figure III.2.2.2 The Estimated Backward Bending Supply Curve (Belzer and Sedo, 2018)



The vertical axis represents the mileage pay rate while the horizontal axis represents the work hours of a driver. From A to B, the substitution effect dominates the income effect, as the pay rate increases and the work hour increases or drive more. From B to C, the income effect dominates the substitution effect or drive less. B is the tipping point on the graph, which represents the reservation rate for that driver. Therefore, if the market-clearing price is at point A, where HOS rule of 60 hours per 7 days stands, and a typical driver has a target income at point B subject to other constraints, then the driver has the incentive to drive beyond 60 hours while violating the HOS rules. That often translates into more HOS violations, fatigued driving, and poor health status, which all add up to the risk of a crash. If the employer can increase the mileage pay rate to point C, then that representative driver will drive less and follow the HOS regulation (Michael H. Belzer, Daniel A. Rodriguez and Stanley A. Sedo, 2002, Michael H. Belzer and Stanley A. Sedo, 2018, Takahiko Kudo and Michael H. Belzer, 2019).

Based on this theoretical background above, the hypothesis we are testing in this chapter is whether or not the HOS compliance violations correlate crashes for intrastate property carriers. If the estimated result is statistically significant, we then test whether the impact is transitory or permanent. Furthermore, we will validate the relationship between compensation and crashes, since the recent studies show a significant impact.

Data and Variables

Our primary data source is the Motor Carrier Management Information System (MCMIS) dataset, updated and released monthly by the Federal Motor Carrier Safety Administration (FMCSA), in which the data mainly comes from field offices through SAFETYNET[6], Compliance Analysis and Performance Review Information (CAPRI), and other sources. The monthly release includes four key datasets: Census, Inspection,

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[6] SAFETYNET is a database management system that allows entry, access, analysis, and reporting of data from driver/vehicle inspections, crashes, compliance reviews, assignments, and complaints.

Violation, and Crash for both interstate and intrastate carriers. Because all Census data are at the firm level and carriers often update once a year or every two years, we choose to do our analysis at the firm level using annualized numbers. In this chapter, our sample period is from 2015 to 2018, inclusive, while the carrier type is still restricted to intra-state property carriers.

Table III.3.1.1 Carriers by Type

Year/Carrier Type	A	B	C	Grand Total
2015	49,508	**2,078**	**30,219**	81,805
2016	150,966	**3,552**	**30,937**	185,455
2017	265,282	**5,361**	**57,231**	327,874
2018	353,759	**6,785**	**84,139**	444,683
OBS	**819,515**	**17,776**	**202,526**	**1,039,817**

In our merged census dataset, there are 1.04 million total monthly observations over four years, as shown in Table III.3.1 above, covering a sample period from 2015 to 2018 while excluding all passenger carriers. For carrier operation types, FMCSA defines interstate carriers as type A, intrastate non-hazmat carriers as type B and intrastate hazmat as type C. Since we are focusing on the intra-state carriers, this decision reduces the number of observations to 220,302, which accounts for 21% of all carriers in our merged MCMIS database over four years. In addition to the carrier operation type, the census dataset also includes motor carrier information such as DOT numbers, hazmat flags, passenger-carrier flags, locations, MCS 150 update date, reported vehicle mileage traveled (VMT), the corresponding VMT year, number of power units reported, and number of drivers reported. Carriers submit and update carrier information, such as legal name, number of drivers, and other characteristics, every year or two, on the MCS 150.

The Inspection dataset includes incident level information regarding the different levels of BASIC related inspections, which are relevant to unsafe driving, Hours-of-Service compliance, driver fitness, and vehicle maintenance. The dataset includes the DOT number of the carrier, report state, and the date, which are used for mapping.

The Violation dataset includes five BASIC-related violations. The unsafe driving violation refers to careless or reckless driving, such as speeding. Hours-of-Service (HOS) compliance violation is mostly exceeding drivable hours or false logging. Driver fitness violation is typically driving without a commercial driver's license (CDL) due to medical conditions. Controlled substances/alcohol violation means driving under the influence of alcohol or drugs. Vehicle maintenance violation is commonly caused by poor maintenance of the truck.

Table III.3.2 Top 10 HOS Compliance Violations

HOS Violation Codes	SECTION_DESC	% of total
3958	Record of Duty Status violation (general/form and manner)	9.56%
3953A2PR	Driving beyond 14 hour duty period	6.93%
3953A3PROP	Driving beyond 11 hour driving limit in a 14 hour period	6.34%
3953A2PROP	Driving beyond 14 hour duty period	6.20%
3953A3PR	Driving beyond 11 hour driving limit in a 14 hour period	5.68%
3953A3II	Driving beyond 8 hour limit since the end of the last off duty or sleeper period	5.35%
3958E	False report of drivers record of duty status	5.19%
3958F01	Drivers record of duty status not current	4.82%
39522H4	Driver failed to maintain supply of blank drivers records of duty status graph-grids	4.63%
3958A	No drivers record of duty status when one is required	4.54%
Subtotal		59.24%

Table III.3.2 shows the top 10 HOS compliance violations by weight in 2018, which accounts for almost 60% of all HOS violations. Although violation codes are slightly different due to the classification and the local interpretation, they all fall into two broader categories: driving beyond the daily limit of 11 hours or working beyond 14 hours and false logging, which could potentially serve the same purpose of driving more hours than is allowed. According to the latest HOS regulation, all property-carrying drivers cannot drive beyond 11 hours after 10 consecutive hours off duty, nor can they legally drive beyond 14 hours per day when taking non-driving on-duty hours into account.

The Crash dataset includes incident level data such as fatalities, injuries, light conditions, and weather conditions. This dataset also has the DOT number, state, and date, which are used for mapping in this study.

In addition to these four datasets from MCMIS, we get the wage dataset from the Occupational Employment Statistics (OES) Survey by state and occupation, and the population data from the U.S. Census Bureau. OES provides an update on the median wage of each occupation in the US in May each year, which also includes a wide range of classification for a single industry. In this study, it is most Relevant to look at truck transportation (NAICS 484000), and we narrow down to "Heavy and Tractor-Trailer Truck Drivers" (OCC 53-3032).

Furthermore, we choose the median hourly pay of each state as our wage variable since we believe the wage of intrastate carriers will not be materially different from each other due to vivid competition and high turnover in the market. Meanwhile, the hourly rates do differ across states due to the cost of living. All wage data are in nominal terms, so we used the GDP deflator to calculate the real hourly wage rate, setting 2015 as the base year.

Descriptive Statistics

The Federal Motor Carrier Safety Administration (FMCSA) commits to preventing commercial motor vehicles (CMV) related injuries and fatalities. Currently, the Safety Measurement System (SMS) is the primary tool used to detect motor carriers with safety compliance issues. SMS includes 899 possible violations that may arise from roadside inspections and puts them into six categories: Unsafe Driving, Hours-of-Service Compliance, Vehicle Maintenance, Controlled Substances/Alcohol, Hazardous Materials Compliance, and Driver Fitness.

Table III.4.1 shows the descriptive statistics of each variable over the sample period from 2015 to 2018. The total number of observations is 43,606 since we exclude the carriers with the dual status of interstate and intrastate carriers, as the goal of the study is to focus on the intrastate carriers. Initially, there were quite a few duplicates in the raw dataset, and we used multiple layers of cleaning technique to remove the duplicates for each year.

Our dependent variable is the count of crashes, while our independent variables are 5 BASICs and hourly wage (in 2015 dollars). The other three variables are the control variables. Also, for BASIC violations we standardize the measure by dividing the number of violations by power units in the same year.

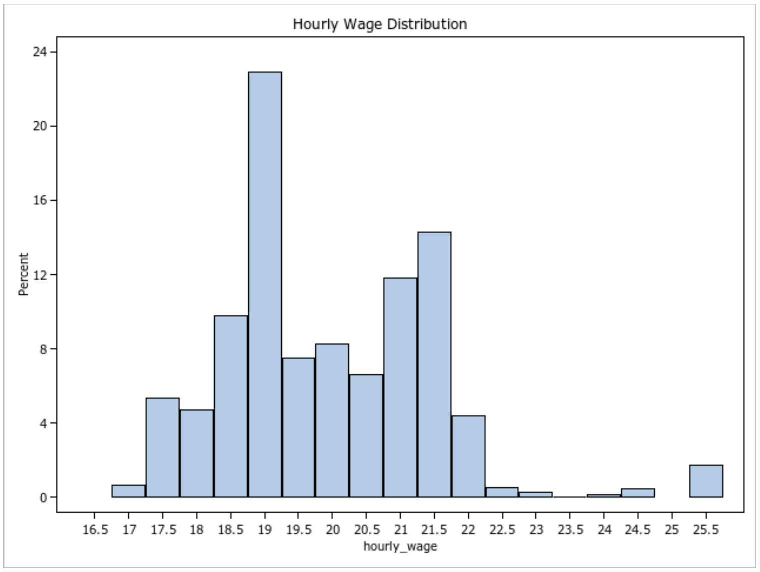
Table III.4.1 – Descriptive statistics 2015-2018

Summary statistics						
Variable	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**	**Label**
CRASHES	43606	0.24	1.49	0	107	Number of crashes
HOS	43606	0.11	0.88	0	38	Number of HOS compliance violations
UNSAFE	43606	0.15	0.73	0	28	Number of unsafe driving violations
DR_FIT	43606	0.15	0.80	0	26	Numebr of driver fitness violations
SUBT	43606	0.00	0.08	0	6	Number of controlled subtances violations
VM	43606	2.64	8.15	0	221	Number of vehicle maintenance violations
WAGE	43606	19.93	1.53	17	26	Median hourly wage in the carrier's state
LPop_density_m2	43606	4.86	1.19	0	9	Population density in 2015
LVMT	43606	10.42	1.62	7	22	Reported VMT
HM_FLAG2	43606	0.02	0.13	0	1	Hazmart flag

Most of the variables are the count of occurrence at the carrier level. The nominal hourly wage has a mean of $19.93 in 2015 dollars, which is seemingly lower than the average hourly earnings of $27.53 in the US in 2018 according to the U.S. Bureau of Labor Statistics. However, production workers have a 40-hour workweek, while a typical long-haul employee driver had 65 hours of work in 2010, according to the NIOSH survey (Takahiko Kudo and Michael H. Belzer, 2019). Therefore, we cannot simply conclude that drivers are underpaid compared to average workers. Because truck drivers have an option to drive more and pursue higher incomes, but often that is linked to FMCSA BASIC violations, which will adversely affect their safety. Inevitably, earning is the main driver of truckers' safety.

Figure III.4.1 below shows the hourly wage distribution over our sample period from 2015 to 2018, all in 2015 dollars. The mean is 19.93 while the mode is around 19, so we would expect the long-term market-clearing wage falls in the range from $19-$20 per hour, given the OES hourly rates.

Figure III.4.1 Hourly Wage Distribution



From Michael H. Belzer and Stanley A. Sedo (2018), we learn that the labor supply curve in the trucking industry is backward bending, so there is a turning point greater than which drivers reduce labor in exchange for leisure or other goods. In other words, if the price elasticity of labor supply is elastic, then the substitution effect dominates the income effect, and drivers will work more when income increases. On the flip side, when the income effect dominates, then the driver will work less when the wage rate increases.

On average, the mean crash counts vary by year due to the difference in the number of observations, as we have a relatively large sample for 2017 and 2018. The count of crashes is purely based on distinct incident IDs, so the double-counting issue in the current study has been minimized. Since these are all local police-reported crashes, the total number of crashes is likely understated, but on the other hand, those unreported crashes are presumably less severe than the reported ones.

Meanwhile, some states may have a record of understating crashes, and that will be partially captured by our control variables.

In our sample, HOS compliance violation had a mean of 0.24 and a standard deviation of 1.49, meaning 90% of the intrastate motor carriers had fewer than 3 crashes, while for a single carrier, the maximum number of HOS violations per truck can be as high as 38. Unsafe driving violations have a mean of 0.15 and a standard deviation of 0.73, meaning 90% of the intrastate trucking companies had fewer than 2 violations, while for a single carrier, the maximum number of violations per power unit can be as high as 28. In comparison to other BASICs, HOS violations have the second-highest per truck occurrence. Driver fitness violations have a mean of 0.15 and a standard deviation of 0.8, meaning 90% of the intrastate trucking companies had fewer than 2 violations, while for a single carrier, the maximum number of violations can be as high as 26.

Controlled substances/alcohol violations have a mean close to 0, and this appears to be the least common violation in the sample period with a low mean and a low standard deviation, suggesting the intrastate carriers may either have limited exposure to drugs and alcohol due to predetermined schedule or it is harder for the enforcer to capture such violations. In other words, the authorities are so tough on drug and alcohol violations and the standards are so high that almost no drivers get caught anymore, at least in active roadside inspections. Probably only spot tests do, like urine tests at random by the firms, which the regulations require, however those may not get into these statistics. Vehicle maintenance violations have a mean of 2.64

and a standard deviation of 8.15, meaning 90% of the intrastate had fewer than 17 violations per truck, while for a single carrier, the maximum number of violations can be as high as 221.

On average, an intrastate property-carrier has 4.33 trucks with a standard deviation of 18.95, which is consistent with the statistics of vehicle maintenance violations and suggests most carriers are small ones with five or fewer trucks while there are only a few giants in the intrastate sector, which drives the standard deviation up, as the largest carrier has 1,273 power units.

Table III.4.1 Distribution of power units in 2017 and 2018

	Percentile and Number of Power Units					
Year	P_50	P_75	P_80	P_85	P_90	P_95
2018	2	3	4	5	8	13
2017	2	4	5	6	9	16

Table III.4.2 shows the distribution of the power units in 2017 and 2018, for 50% of the intra-state property carriers in the sample have two trucks, while 85% of carriers have fewer than six trucks in 2018. In the census dataset, the number of drivers is also included. However, a high correlation exists between drivers and trucks, and we choose the latter one to avoid the multicollinearity issue.

State population density per square mile has a mean of 225 people per square mile and a high of 11,011 heads per square mile in 2015. Reported vehicle mileage traveled has a mean of 33,523 per carrier. The HM flag is an indicator for differentiating hazmat and non-hazmat carriers – 1 for hazmat and 0 otherwise. Hourly wage is in log transformation because we want to estimate the elasticity.

Reported VMT and state population density per square mile are in natural logarithm because that helps to minimize the excessive impact of large numbers.

Consequently, our independent variables are five BASIC violations and hourly pay, while others are the control variables in the model.

Regression Analysis

Takahiko Kudo and Michael H. Belzer (2019) explore the 2010 NIOSH dataset and find the mileage pay rate and employment-based health insurance significantly decrease the probability of moving violations, in which the moving violations are used as a proxy for safety performance because the number of crashes in the NIOSH survey is questionable. The NIOSH survey asked drivers the number of crashes they have experienced during their career instead of during a specified period, while they asked about other variables, such as compensation, in another dimension. More specifically, they asked compensation questions at a yearly level, but hours worked at the weekly level, as of the time of the interview. Besides, they do not dive into the causality between moving violations and crashes due to the same constraint.

In this paper, in contrast, we explore this particulate causality in the intra-state property-carrying sector of the trucking industry from 2015 to 2018 using the MCMIS firm-level data. All variables are mapped with a constraint on the year so that they are more aligned with each other than the NIOSH one. We get our state-level OES wage data from the U.S. Census Bureau for the whole sample period from 2015-2018, which could be more stable and reliable than the NIOSH one, especially for the intra-state carriers. We believe the hourly rate may be materially different across carriers within the state, while differences must exist across states due to the cost of living.

Indeed, each firm has its only uniqueness, such as the leadership and the safety culture, but in Chapter 2, we ignore such uniqueness and assume carriers are mostly the same. In this Chapter, we release the constraint on the carrier's homogeneity by using the random-effect model. Still, we want to test our hypothesis that BASIC violations lead to crashes from a typical firm's perspective over a four-year sample period. Meanwhile, we choose the random effect model over the fixed effect model because we believe that differences across carriers have some influence on the dependent variable. For example, if a carrier has a weak safety culture or no strict background check on new hires, then we would like to treat these factors as unobservable of each carrier or variance across different entities in the random effect model while we could not capture that uniqueness in the fixed-effect model. The Poisson Random Effect Model can be written as:

$$
\begin{aligned}
\log\left(Crashes_{i,t}\right)
&= \beta_0 + \beta_{1,t} \times HOS\,Viol + \beta_{2,t} \times Unsafe\,driving\,Viol \\
&+ \beta_{3,t} \times Driver\,fitness\,Viol + \beta_{4,t} \times Substance\,alcohol\,Viol \\
&+ \beta_{5,t} \times Vehicle\,maintenance\,Viol + \beta_{6,t} \times Log(Hourly\,wage) \\
&+ \beta_{7,t} \times Log\,(Population\,density) + \beta_{8,t} \times Log\,(VMT) \\
&+ \beta_{9,t} \times Hazmat\,flag + \mu_i + \varepsilon_{i,t}
\end{aligned}
$$

Where

μ_i is the between-carrier error, capturing carrier i's unique characteristics

$\varepsilon_{i,t}$ is the within-carrier error

In addition to the Poisson random effects model we also include the two pooled models for comparison.

Estimated Results

Table III.1 Dependent Variable Log (Crashes)

Column	A		B		C		D	
	NB - 2018		Poisson pooled 2015-18		NB pooled 2015-2018		Poisson RE 2015-2018	
Variable	**Parameter Estimate**	**Pr > |t|**	**Parameter Estimate**	**Pr > |t|**	**Parameter Estimate**	**Pr > |t|**	**Parameter Estimate**	**Pr > |t|**
Intercept	0.30	0.88	-0.02	0.98	-2.57	0.04	-2.42	0.06
HOS	0.25	0.01	0.09	<.0001	0.06	0.11	0.09	0.01
UNSAFE	0.22	0.01	0.04	0.11	0.34	<.0001	0.26	<.0001
DR_FIT	0.02	0.75	0.03	0.18	0.01	0.75	0.04	0.28
SUBT	0.33	0.63	0.12	0.26	0.46	0.31	0.83	0.03
VM	0.04	<.0001	0.01	<.0001	0.04	<.0001	0.03	<.0001
lwage	**-3.16**	**<.0001**	**-3.09**	**<.0001**	**-1.83**	**<.0001**	**-1.80**	**<.0001**
lPop_density_m2	0.19	<.0001	0.13	<.0001	0.21	<.0001	0.20	<.0001
LVMT	0.56	<.0001	0.61	<.0001	0.47	<.0001	0.45	<.0001
HM_FLAG2	0.77	0.01	0.97	<.0001	0.92	<.0001	0.96	<.0001
Dispersion	17.37		1.00		26.52		0.33	
Full Log Likelihood	-2088		-29538		-15064		-15480	

Table III.1 summarizes the estimated results of different samples and models, in which column A shows the same result that we presented in Chapter 2, and we want to use that as the benchmark to other models (Column B to D) in Chapter 5. Column B to C show results of pooled Poisson and pooled negative binomial model (NB), which utilize all information in the MCMIS dataset from 2015 to 2018. The last column exhibits the results from the Poisson random effects model (Poisson RE), which is our preferred model in this chapter. Although the parameters of Poisson RE and NB are close to each other, Poisson RE allows the firm's uniqueness over time. Therefore, the results are more precise.

Overall, most explanatory variables are consistent across models. In our full sample, the total number of observations is 43,606 over four years.

The HOS violation has a positive sign across all models, which is aligned with the benchmark. Intuitively, we would think HOS related violations such as driving over the time limit would lead to fatigue and thus increase the probability of crashes in the long run. The current result suggests a 1 unit increase in HOS violations per vehicle correlates to 1.09[7] more crashes.

The estimated parameter of the unsafe driving violation has a positive sign, and the estimated parameter is statistically significant at the 1% level, which is consistent with our expectation and the OLS result in Chapter 2. We think this violation is mainly behavior-driven, or it heavily relies on the driver's driving habit. From a carrier's perspective, it will be hard to change the driver's unsafe driving habit, such as changing lanes without using the turning lights or not fastening the seat belt in the short run. Therefore, these long-lasting bad driving habits would eventually lead to crashes. However, according to the efficiency wage hypothesis, carriers do have an option to offer a better than the market wage rate to attract high skilled drivers and thus fundamentally lower the unsafe driving behaviors at the carrier level. According to the preferred model, 1 unit increase in unsafe driving violations per vehicle correlates to 1.3 more crashes.

The estimated parameter of driver fitness is not statistically significant at the 10% level. A positive sign would suggest drivers at the carrier keep driving under poor health conditions, which correlates to more crashes in the end. As we discussed above, most intrastate carriers are small ones with 5-6 drivers, while the estimated suggest they are

[7] Log(crashes)=0.09, crashes=exp(0.09) = 1.09

taking the risk of violating laws in exchange for work and income, which implies they are not satisfied with the current level of income. In other words, the substitution effect still dominates the income effect. From a policy perspective, this is an economic concern rather than a regulatory concern. FMCSA could tighten the enforcement to take away more commercial driver's licenses from the drivers with poor health conditions, but this action will not fundamentally resolve the root cause; those drivers will still try their best to dodge the regulations and drive more at risk.

On the other hand, if the carrier increases the hourly wage rate, then the income effect will weigh more and eventually dominates the substitution effect and consequently improve the driver's health and lower crashes.

The estimated parameter of the controlled substances and drug violation has a positive sign and is statistically significant at the 5% level in our preferred model but not statistically significant at the 10% level in others, which is consistent with what we have shown in Chapter 2. This violation is similar to the unsafe driving one since both replies on drivers' characteristics. However, an addict will not easily change the adverse behaviors in the short run. Therefore, the carrier may want to pay a higher than the market-clearing wage to attract non-addictive workers.

The estimated parameter of vehicle maintenance has a positive sign, and it is statistically significant at the 1% level, which is aligned with our findings in Chapter 2. Although the magnitude of the parameter looks relatively low, each incremental maintenance violation does add risks of crashes. Drivers and carriers must take maintenance violations seriously. A 393.75(c) violation (tire-other tread depth less than 2/32 of an inch measured in a major tread groove) is as critical as a 396.5(b) violation (Oil and/or grease leak).

The sign of hourly wage is negative and statistically significant at the 1% level across all models, indicating a reliable predicting power. This result is consistent with our expectations and aligned with findings in the current literature. That is, drivers react to the change in compensation; as the pay increases, the opportunity cost of crashes increases, hence they have an incentive to drive more safely (Michael H. Belzer, Daniel A. Rodriguez and Stanley A. Sedo, 2002, Michael H. Belzer and Stanley A. Sedo, 2018, Michael R. Faulkiner and Michael H. Belzer, 2019, Takahiko Kudo and Michael H. Belzer, 2019, Daniel A. Rodriguez, Felipe Targa and Michael H. Belzer, 2006). According to the current estimate, the elasticity is -1.8 over the sample period from 2015 to 2018 for intrastate carriers, meaning that 1% higher in hourly wages correlate to 1.8% fewer crashes. Therefore, it is important to take this economic factor into account from a regulator's perspective.

The state population density is a control variable which aims to capture some state-level characteristics. The estimated parameter is statistically significant at the 1% level across all models. We would assume a crash is more likely to happen in California than in Alaska, given the controls. In the future study, better individual state control variables will be introduced in subsequent research, to examine state effects beyond income and to improve precision of the estimates.

The estimated parameter of vehicle mileage traveled has a positive sign, and it is statistically significant at the 1% level. Since we are focusing on the intra-state carriers, the reported VMT by each carrier represents mileage traveled within the state of operation. The current results also confirm the more mileage driven, the more crashes may occur, which is consistent with our expectation.

The estimated parameter of the hazmat flag has a positive sign, and it is statistically significant at the 5% level, which indicates the current FMCSA classification of the hazmat and non-hazmat matter. Presumably, hazmat drivers would have more training as we would expect them to have fewer crashes. However, the current results show the opposite result.

Discussion on the efficiency wage

In the previous section, we discussed the currently estimated results and explored the causality for intra-state property carrier-related crashes, over the sample period from 2015 to 2018. We find that not all BASIC violations are predictive of crashes, while the hourly pay indicates a strong and consistent predicting power.

Therefore, we conclude that the hourly wage does matter to drivers at the carrier level in our sample period from 2015 to 2018. If the wage rate increases, the number of crashes decreases.

To test further, we split the full sample into three groups: high pay, mid pay, and low pay carriers. As the distribution shown in Table 3.5.2, we expect the four-year market average rate falls between $19 and $20, and we further calculate the percentile of the hourly wage. The 50th percentile gives $19.59, so we use this rate as the market average. We define the high pay group as those who pay 20% higher than the market average and low pay as those who pay 20% lower than the market average; the rest is in the mid pay group.

Table III.7.1 Subgroup Estimated Results

Variable	NB - 2018 Parameter Estimate	NB - 2018 Pr > |t|	Highpay Parameter Estimate	Highpay Pr > |t|	Midpay Parameter Estimate	Midpay Pr > |t|	Lowpay Parameter Estimate	Lowpay Pr > |t|
Intercept	0.296	0.881	3.179	0.774	5.010	0.321	-11.031	0.222
HOS	0.255	0.010	0.153	0.545	0.171	0.128	0.489	0.050
UNSAFE	0.221	0.013	0.215	0.364	0.144	0.202	0.458	0.034
DR_FIT	0.023	0.752	-0.140	0.414	0.118	0.243	-0.132	0.568
SUBT	0.328	0.634	0.712	0.571	-1.092	0.454	0.819	0.644
VM	0.038	<.0001	0.053	0.122	0.037	0.000	0.005	0.836
LWAGE	**-3.164**	**<.0001**	**-3.938**	**0.260**	**-4.903**	**0.004**	**0.458**	**0.881**
LPop_density_m2	0.193	<.0001	0.133	0.104	0.275	0.002	0.426	0.000
LVMT	0.558	<.0001	0.535	<.0001	0.571	<.0001	0.518	<.0001
HM_FLAG2	0.768	0.007	0.623	0.368	0.723	0.065	0.887	0.089
Dispersion	17.372		24.470		15.617		15.448	
Full Log Likelihood	-2088.4		-1079.4		-2885.0		-1025.0	

Table III.7.1 shows the estimated parameters of different groups among intra-state carriers in 2018, while NB column still serves a benchmark. For all, the hourly wage matters because the signs of high pay and mid pay groups are negative and statistically significant at the 1% level. However, the estimated parameter of low pay is statistically significant at the 10% level. In terms of the marginal impact, the high pay group has an elasticity of -3.9 in 2018, while mid pay group has an elasticity of -4.9. Holding other things constant, an identical increase in hourly wage will lead to a more favorable (safer) outcome from the mid pay group.

To marginally reduce crashes, it will be more cost-effective to increase the hourly wage of the mid pay group because that gives a greater reduction on crashes as drivers are more sensitive to the difference in hourly wages. Alternatively, we could use the mid-point method to calculate elasticity, and we calculated the wage elasticity of crash using

2017, and 2018 mean wage and crashes of each firm, who updated the MCS150 file in both years. The median elasticity in the sample is -5.84[8], which is close to the elasticity in Michael H. Belzer (2012). The estimated wage elasticity of crash is elastic and negative, meaning that a 1% increase in hourly wage is associated with 5.84% lower crash rate in our sample. This result is aligned with the elasticity of mid pay group.

The low pay group (20% below the market average) is inelastic to the difference in hourly wages. One explanation can be the hourly wage is already low, so the opportunity cost of crashes and losing a trucking job is relatively low than the other two groups. Therefore, a marginal increase in hourly wage is not strong enough to incentivize safety driving for the low pay group.

One could argue the OES hourly wages are at the state level, so this variable is really capturing the impact of state wealth instead of driver's wage. We test a model with state-level GDP per capita replacing the hourly wage. The results show a negative sign and strong statistical significance. However, the elasticity is -1.32 for 2018 meaning that GDP per capita as a proxy for state wealth is important, but truckers are more sensitive to the change in hourly wage than state wealth in general.

The sign of HOS violations is positive for all, while the parameters are only statistically significant at the 5% level for the low pay group, suggesting that both groups react to HOS violations. The sign of unsafe driving is positive, and the magnitude is larger for low pay carriers, which would suggest that we need a minimum wage in trucking (a

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[8] $\text{wage elasticity of crash} = \frac{(Crashes_{2018} - Crashes_{2017})/average(Crashes_{2017\sim 2018})}{(Hourly\ Wage_{2018} - Hourly\ Wage_{2017})/average(Hourly\ Wage_{2017\sim 2018})}$

"safe rate") designed to force the bottom carriers (and drivers) to a higher level of performance.

Overall, we think that in our sample, the high pay group of carriers compared with small carriers. That is not precisely parallel unless there is an implied difference, which suggests the high pay group of carriers exhibits better safety awareness than the small carriers, while the main driver is probably not the regulations but the difference in compensation. In other words, compensation pays for safety while the favorable marginal impact will be higher for currently low pay carriers.

One remaining question is: does the firm size matter? Conventionally, we would think any firm with 5 or more drivers as large firms in intrastate trucking, as the percentile shows that 85% of the intrastate carriers in our sample had 5 or fewer drivers in 2018 or 6 in 2017, in table III.7.2. Hence, we decide to use 50 (a more substantial number) to see if there is any systematic difference in hourly wage due to carrier size in our sample. In other words, we define large firms as carriers with 50 or more drivers.

Table III.7.2 Distribution of drivers in 2017 and 2018

	Percentile and Number of Drivers					
Year	P_50	P_75	P_80	P_85	P_90	P_95
2018	2	3	4	5	7	12
2017	2	4	4	6	8	15

Figure III.7.1 Hourly Wage Distribution (Subgroup)

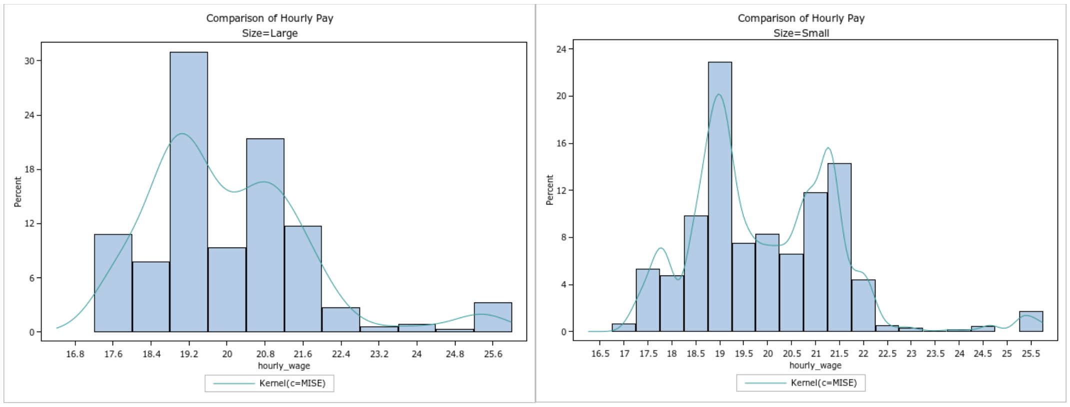

Table III.7.1 shows the distributions of the hourly wage of large carriers and small carriers. The distributions look similar, so we cannot conclude there is a premium paid by large carriers.

Conclusion

In this chapter, we test the relationship between BASIC violations and crashes, and validate the relationship between compensation and safety, implementing longitudinal analysis for a sample period from 2015 to 2018. The estimated results show that compensation is the most consistent and significant influencer of crashes, while the higher than the market average compensation makes a difference in our subgroup analysis. Based on our estimated elasticities, a 1% higher hourly pay rate correlates to 1.8% fewer crashes. In our subgroup analysis, low pay carriers are inelastic to the difference in hourly wages and the high pay group is sensitive to the difference, but the mid pay group is the most sensitive one with an elasticity of -4.9 which could lead to a more considerable reduction in crashes given the same increase in hourly pay. In other words, it is more cost-effective for mid pay carriers to offer a compensation raise to improve their safety performances.

Overall, we think this suggests that though FMCSA should keep their current enforcement strategy (enforce on the BASICS while targeting the carriers they think are unsafe), however, not all BASICs are predictive of crashes. Instead, they could obtain stronger safety outcomes by tracking driver pay (as the 2017 NAS report recommends) and take carrier pay into effect in their evaluation of safety effectiveness (Panel on the Review of the Compliance Safety and Accountability, Committee on National Statistics and Transportation Research Board, 2017). Meanwhile, for all intrastate carriers, if the mid pay group can raise hourly pay, then the safety performance will be improved the most for the industry.

CHAPTER 4 SAFETY MEASUREMENT AND ECONOMIC IMPACT

Introduction and Literature

The Federal Motor Carrier Safety Administration (FMCSA) has a commitment to prevent commercial motor vehicles (CMV) related injuries and fatalities. Currently, the Safety Measurement System (SMS) is the primary tool used to detect motor carriers with safety compliance issues. SMS includes 899 possible violations that may arise from roadside inspections and puts them into six categories: Unsafe Driving, Hours-of-Service Compliance, Vehicle Maintenance, Controlled Substances/Alcohol, Hazardous Materials Compliance, and Driver Fitness. There is a metric of weighted frequencies of violations for each of these groups. In addition to these six FMCSA provides a weighted crash frequency metric. These seven metrics are referring to as the Behavior Analysis and Safety Improvement Categories (BASICs). For each carrier with sufficient inspections, violations and crashes available in FMCSA's Motor Carrier Management Information System (MCMIS), FMCSA computes seven metrics for each carrier and compares the results to the thresholds to determine the level of interventions, including warning letters, on-site investigations, fines and suspension of business.

The Panel on the Review of the Compliance Safety and Accountability, Committee on National Statistics and Transportation Research Board (2017) reviewed the existing Safety Measurement System (SMS) and concluded that the current SMS structure is reasonable, but FMCSA needs to adopt a more statistically validated approach that might be more objective and consistent, and enhance the transparency of the evaluation. A few stakeholders and outside reviewers have criticized SMS for making use of variable assessments, not excluding crashes where the CMV driver is not at fault, using universal measures for all carriers, and using measures that are not predictive of a carrier's future crash frequency. The panel recommends that the FMCSA consider a two-dimensional measure, which takes account of both SMS score and percentile rank. The percentile ranks should be calculated both conditionally within safety event groups and over all motor carriers. However, the panel fails to answer whether FMCSA should make all SMS percentile ranks public.,

Moreover, the data quality of MCMIS is also challenged by the panel. Because there are consistently underreported crashes and different reporting standards across states. Besides, the dataset lacks deterministic information such as turnover rate, type of cargo, compensation, and objective VMT.

However, we believe the panel fails to address the economic impact of the recommended changes, as the main emphasis is on the safety measurement. Still, it is worthwhile to help carriers and the public to understand the economic impact of crashes and thus reduce the incentives for violations, on average. Also, they suggest building an item response theory (IRT) model over the following two years.

Lawrence J Blincoe et al. (2002) analyzed the reported and unreported motor crashes in the United States in 2000 and estimated a total economic cost of $230.6 billion to society, which was equivalent to $820 per capita or 2.3% of the gross domestic product (GDP) in 2000. More specifically, they split the total cost of the motor crashes into eight components: market productivity, medical, emergency services, property damage, household work loss, insurance admin, workplace cost, legal costs, and travel delay. According to their estimation, on average, each fatality costs a present value lifetime cost of $977,000 in 2000 dollars, using the census data in the Fatality Analysis Reporting System (FARS). Public revenues paid for 9 percent of the total economic cost, which adds over $200 tax burden on every household in the U.S. In addition, they pointed out that crashes involving at least one driver exceeding the legal speed limit cost $40.4 billion. After a decade, they revised the estimates using 2010 data and found the economic cost of motor carrier crashes totaled $242 billion in the United States, while the total social cost in terms of quality-of-life valuations is $836 billion, which equates to $156 per household. (Lawrence Blincoe et al., 2015)

Eduard Zaloshnja and Ted Miller (2002) followed Blincoe et al. (2002), using FARS and General Estimates System (GES) data, and estimated the average economic cost of a police-reported large truck crash averaged $59,153 in 2010, which represents the present value of all costs over the victim's expected life after a truck crash. The cost components are like those in Blincoe's paper, and they define the large truck as a truck more than 10,000 pounds. Further, they found the costs per crash with injuries was around $167,730 while per crash with fatality was $4.2 million per crash, and they concluded the average cost of large truck crashes in 1997-1999 was more than $19.6 billion in 2000 dollars, while the estimated cost excluded a few related costs such as mental health care costs, cargo delays and earnings lost by family and friends for taking care of the victims. In two years, Eduard Zaloshnja and Ted R Miller (2004) revised the study on the costs of large truck-involved crashes by truck type in the US, using a pool of reweighted data, and found the crash costs per 1,000 miles traveled were $157 for single-unit trucks, $131 for single combination trucks and $63 for multiple-combination ones.

Saltzman and Belzer (2007) gave a comprehensive overview of the truck driver occupational safety and health status after the change of hours-of-service rules for commercial truck drivers in 2004, which increases the daily allowable driving time from 10 to 11 hours. They reviewed strong statistical evidence on the negative relationship between compensation and safety, suggesting high compensation could reduce the probability. In other words, the change in HOS induces truck drivers to drive more as the compensation does meet driver's expectation since the Fair Labor Standard Act does not apply to truck drivers while drivers often are paid by miles but not hours meaning that they are not compensated for non-driving activities such as waiting at the docks. Therefore, truck drivers, especially the long- haul ones, have a strong incentive to drive more either by dodging the HOS regulation or breaking it. Drivers could drive 11 hours a day, complete 70 hours of duty time at day 5 then take a 34-hour mandatory reset then squeeze out another 14 hours on day 7 to get a total of 84 work hours in seven consecutive days, which in turn causes sleep debt, fatigue and ultimately crashes. They also brought up the fact that there was no existing data on commercial truck driving in the FMCSA at that time, which could be crucial to future studies, as more research would be needed for trucker's safety and health.

Eduard Zaloshnja and Ted Miller (2008) used the 2001-2003 Large Truck Crash Causation Study (LTCCS) data, which was the only sample with injuries and associated medical records at that time, for estimating injury costs of the large truck crashes and the 1982-1986 NHTSA's National Accident Sampling System data for other type of costs, which was the same dataset they used for their 2002 paper. With the updated dataset, they found on average the total cost per large truck crash of $91,112 was 53% higher than that in their 2002 paper, which they believed was mainly due to inflation from 2000 to 2005 and the rest was because of the change in the severity mix of injury. However, the Inflation was low at the period, so this may be caused by the sampling bias.

In the following year, Eduard Zaloshnja and Ted R. Miller (2009) used the same LTCCS dataset to estimate the cost of crashes due to road conditions in the U.S. in the year 2006, in which they calculated costs of crashes where road conditions contributed by states. On average, they concluded their estimated comprehensive cost of crashes due to road conditions was $217.5 billion in 2006, representing 43.6% of the total crash cost, who also listed the top four factors of crashes as road conditions, alcohol usage, speeding and non-usage of seat belts.

Peter F Swan and Michael H Belzer (2013) estimated the crash cost per VMT of the trucking, which diverts from the Ohio Turnpike for paying the toll in Ohio from 2002 to 2006, using crash data, highway classification, and traffic statistics. Their empirical results suggested the expected crash cost per million VMT has a range from $81,226 to $332,533, which varies by road segment, while the total incremental crash cost from diversion was about $39.5 million, which far exceeded the revenue benefit of tolling.

Curtis Florence et al. (2015) updated the CDC estimation on lifetime medical and work-loss costs of fatal injuries in the U.S. in the year 2013. The fatal injury rate in that year was 61 per 100,000 population, while the corresponding lifetime total cost was more than $214 billion, counting one-third of the medical and work-loss costs of $671 billion for all injuries.

Lucija Muehlenbachs et al. (2017) used the data from Crash Reporting System (CRS) by PennDOT, geographic information system (GIS) technique to predict most likely truck routes, and fixed effect regression model to estimate the accident externality from trucking. They argue that although a truck may not directly cause an accident, its presence on the road will increase the likelihood of crashes for others when trying to surpass the truck against the oncoming traffic in Pennsylvania, which leads to a $0.48 insurance premium on all new enrollees.

Harmon, Bahar, and Gross (2018) combined the methodologies and procedures from the past 10 years of research and conducted a highway safety benefit-cost analysis, which aimed to describe the national crash costs and provided estimations for each state as well as the national level. According to their results, the comprehensive crash unit costs with a fatality is about $11.3 million while the costs of a crash with different degree of injuries has a range from $655,000 to $125,600 per crash on the national level, while the costs vary across states.

Mohammad Mahdi Rezapour Mashhadi et al. (2018) used the violation and the crash data from 2011-2014 in Wyoming to study the impacts of various variables on single truck crashes and multiple truck-involved crashes. Based on the logistic regression results, they found for single truck crashes being female, driving on the dry-road condition, speeding, and having a distraction in the cabin were the statistically significant factors that increased the probability of crashes, while for multiple crashes the leading factors were speeding and driving during weekends. Further, they concluded that truckers played a dominant role in violations like following too close and led to about 26% of all causes of multiple vehicle crashes in the data. In the same year, Mohammad Mahdi Rezapour Mashhadi, Shaun S Wulff and Khaled Ksaibati (2018) used the same dataset to predict at-fault truck crashes in Wyoming. They concluded that local residency and time of violation were two significant crash predictors in Wyoming because non-local truckers were more likely to have speeding and HOS related violations while at off-peak hours, truck drivers had a higher odd of risky driving and violating HOS regulations.

In this chapter, we aim to follow recommendations by the panel discussion in Panel on the Review of the Compliance Safety and Accountability, Committee on National Statistics and Transportation Research Board (2017) and utilize the OES wage data along with the MCMIS one to build an alternative statistical model to predict carrier's marginal probability of crashes and associated the economic impact of crashes in absence of the IRB model, which could take a few years in development. In other words, we are going to build a statistical model based on the truck-level analysis and aggregate to the carrier level and then compare the outcomes with the existing SMS to see if there is any efficiency gain in data utilization, which has not been done before. Furthermore, we try to provide drivers and carriers a more comprehensive view of the economic impact and hope the increased awareness will reduce the incentive of violations over time. We also test the effectiveness of the current crash-related warning letters and propose our alternative statistical method to promote the efficiency of the MCMIS data usage.

Data and Methodology

Data

Our primary data source is the merged Motor Carrier Management Information System (MCMIS) dataset, updated and released monthly by the Federal Motor Carrier Safety Administration (FMCSA), in which the data mainly comes from field offices through SAFETYNET[9], Compliance Analysis and Performance Review Information (CAPRI), and other sources. The monthly release includes four primary datasets: Census, Inspection, Violation, and Crash for both interstate and intrastate carriers.

The Census dataset includes 1.04 million Interstate, Intrastate Hazmat and Intrastate Non-Hazmat Motor Carriers observations over four years, including DOT number, carrier operation type, hazmat, and non-hazmat flag, passenger-carrier flag, locations, MCS 150[10] update date, reported vehicle mileage traveled (VMT), the corresponding VMT year, number of power units reported and number of drivers reported. FMCSA defines interstate carriers as type A, intrastate hazmat carriers as type

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[9] SAFETYNET is a database management system that allows entry, access, analysis, and reporting of data from driver/vehicle inspections, crashes, compliance reviews, assignments, and complaints.

[10] MCS 150 is the file that every carrier uses to apply for the DOT number, and FCMSA requires carriers to update this file if there is any change in business such as legal name, address, number of drivers…etc.

B, and intrastate non-hazmat as type C. Locations in terms of states are referring to a carrier’s physical location, the mailing location and FMCSA State office with oversight for this carrier. That suggests an interstate carrier may have a presence in multiple states by nature, and it will be tough to distinguish the reported VMT by state or location for each interstate carrier. Therefore, the current study is restricted to intrastate carries. Because for intrastate carriers, those three locations mentioned above should be the same, and the reported VMT also means the mileage traveled in the carrier’s state of operation. In addition, we exclude all passenger carriers in this study because we want to focus on truck drivers, as transporting people is different from hauling commodities. Among all intrastate carriers who updated the MCS150 file in 2018, passenger carriers count 2.2% while trucks count the remaining 97.8%. However, as of July 2019, some intrastate carriers have not updated their VMT for 2018 yet. Thus, the sample size reduces to 15,789 intrastate property carriers in 2018, including hazmat and non-hazmat ones.

The Inspection dataset includes incident level information regarding the different levels of BASIC related inspections, which are relevant to unsafe driving, Hours-of-Service compliance, driver fitness, and vehicle maintenance. The dataset includes the DOT number, state, and date, which can be used for mapping. More importantly, the dataset also includes Vehicle Identification Number (VIN), and this becomes our primary key to mapping with crashes.

The Violation dataset includes five BASIC related violations. The unsafe driving violation is referring to careless or reckless driving, such as speeding. Hours-of-Service (HOS) compliance violation is exceeding legal work hours and false logging. Driver fitness violation is typically driving without a commercial driver's license (CDL) due to medical conditions. Controlled substances/alcohol violation means driving under the influence of alcohol or drugs. Vehicle maintenance violation is commonly caused by poor maintenance of the truck.

The Crash dataset includes incident level data such as fatalities, injuries, light conditions, and weather conditions. Also, the dataset has the DOT number, VIN, report state, and date, which are used for mapping in this study.

In addition to these four datasets from MCMIS, we get the wage dataset from the Occupational Employment Statistics (OES) Survey by state and occupation, and the population data from the U.S. Census Bureau. OES provides an update on the median wage of each occupation in the US in May each year, which also includes a wide range of classification for a single industry. In this study, it is most relevant to look at truck transportation (NAICS 484000), and we narrow down to "Heavy and Tractor-Trailer Truck Drivers" (OCC 53-3032).

Furthermore, we choose the median hourly pay of each state as our wage variable since we believe the wage of intrastate carriers will not be materially different from each other due to competition and high labor market turnover, while the hourly rates differ across states due to the cost of living. For a comprehensive crash unit cost, we use the number from Tim Harmon, Geni Bahar and Frank Gross (2018), who summarized the literature and estimated national crash unit costs for Federal Highway Safety Administration to use in its Safety Guide and Tool.

Methodology

As discussed earlier, one the of primary goals in this chapter is to estimate the probability of a crash for each firm of interest, while the incident-level data are available in the MCMIS datasets, and the size of the carriers varies. Therefore, we decide to run a logistic regression at the vehicle level to get the log(odds) of a crash for a typical vehicle in the sample and then transfer odds to get the probability of a crash for each truck. We take the sum of each VIN's probability within the same firm (Dot number) and aggregate to a firm's probability ratio. Because the more moving trucks a carrier has, the more likely the firm will experience a crash. In other words, the probability is cumulative.

Mathematically, the logistic regression can be written as:

$$Log\left(\frac{Prob}{1 - Prob}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_6 x_6 + \epsilon$$

Where:

Prob represents a typical truck's probability of a crash, while P/(1-P) is the odds

X_1 represents the number of unsafe driving violations within 90 days ahead of the crash

X_2 represents the number of HOS compliance violations within 90 days ahead of the crash

X_3 represents the number of driver fitness violations within 90 days ahead of the crash

X_4 represents the number of controlled substances/alcohol violations within 90 days ahead of the crash

X_5 represents the number of vehicle maintenance violations within 90 days ahead of the crash

X_6 is a controlling variable for hazmat status, 1 for hazmat carrier 0 for non-hazmat

X_7 is another controlling variable for wage rate, OES hourly rates by state

The error term expects zero mean

The transformation of probability can be written as:

$$Prob_i = \frac{e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_6 x_6)}}{1+e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_6 x_6)}}$$

Where:

$Prob_i$ represents the probability of a crash for VIN_i computed by the βs of the typical truck in the industry

Therefore, the carrier's probability can be written as:

$$Prob_k = \sum Prob_i$$

Where:

$Prob_k$ is the cumulative probability of each $Prob_i$ within the firm

We then rank carriers' probabilities from low to high and categorize the carriers into five groups from low risk to high risk. This level of granularity has not been done in the past literature, and this will be the contribution of the current study.

To sum up, we run the logistical model with 2017 intrastate data, and then use the estimated results (statistically significant ones) from the logistic regression to calculate the probability of a crash for each VIN in 2018.

Descriptive Statistics

Table 0.1- Descriptive Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
UNSAFE_VIOL	110,239	0.087	0.299	9,601	0	4
HOS_VIOL	110,239	0.042	0.244	4,623	0	6
DR_FITNESS_VIOL	110,239	0.067	0.294	7,344	0	4
SUBT_ALCOHOL_VIOL	110,239	0.001	0.035	119	0	2
VH_MAINT_VIOL	110,239	1.258	2.000	138,674	0	24
HM_FlAG	110,239	0.077	0.267	8,493	0	1
Hourly_wage	109,596	20.427	1.535	2,238,725	17.7	26.1

Table IV.3.1 shows the descriptive statistics of seven independent variables in the logistic model. For logistic regression, we restrict our sample to intrastate property carriers/VINs in 2017 because that is the primary focus of the current study, and we want to use the estimated parameters to predict the probability of a crash for each VIN in 2018. Ideally, a more generic model using all available information may add precision to the estimated results. However, our hourly wage data is at the state level instead of the individual level, so using intrastate carrier data gives us the best-unbiased estimates.

Furthermore, we believe the hourly wage rate as a proxy for the compensation is essential to the model. Because in the previous chapters, we found a consistent and negative relationship between crash and compensation, which is aligned with the recent findings in other papers by MH Belzer, D Rodriguez and S Sedo (2002), Michael H. Belzer and Stanley A. Sedo (2018), Michael R. Faulkiner and Michael H. Belzer (2019), Takahiko

Kudo and Michael H. Belzer (2019), Daniel A. Rodriguez, Felipe Targa and Michael H. Belzer (2006). The decision of choosing intrastate carriers only reduces our sample size to 109,596 observations, all at the incident level. In the MCMIS dataset, the crashes are grouped into three severity levels ranging from 1 to 3, while 1 means no fatality nor injury, and 3 means massive injuries and fatalities. In our model, we include all severity levels because we believe every crash creates a negative externality to society.

From table IV.3.1, for each incident, the unsafe violation has a mean of 0.087 and a max of 4 violations. The HOS violation has a mean of 0.042 and a max of 6. Driver fitness violation has a mean of 0.067 and a maximum of 4. The mean of controlled substances/alcohol violations is 0.001. Vehicle maintenance violation has the largest variance. The hourly wage has a range from 18 to 27, averaged at 20.42.

Ideally, we want to utilize the full information in the MCMIS Crash dataset. However, there is a constraint on the inspection: not all vehicles had a crash or an inspection record within the quarter, while violations are primarily detected via inspections. The total mapped intrastate property carrier-related crashes reduced to 501 in 2017.

In other words, out of the 10,261 incidents, we observe 501 crashes for 407 mappable intrastate carriers in 2017. According to Table IV.3.2, most crashes in our sample are at severity level 1 or 2.

Table 0.2 Crashes and Severities in 2017

Sample - 2017 Intrastate								
SEVERITY_WEIGHT	CARRIERS	CRASHES	FATALITIES	INJURIES	CARRIERS%	CRASHES%	FATALITIES%	INJURIES%
1	231	271	-	-	57%	54%	0%	0%
2	175	228	21	300	43%	46%	100%	99%
3	1	2	-	2	0%	0%	0%	1%
Total	407	501	21	302	100%	100%	100%	100%

Estimated Results

Table 0.1 - Dependent Variable Log(odds) of a crash

Analysis of Maximum Likelihood Estimates		
Parameter	**Estimate**	**Pr > ChiSq**
Intercept	-1.87	0.006
UNSAFE_VIOL	0.22	0.0949
FATIGUED_VIOL	-0.34	0.1503
DR_FITNESS_VIOL	-0.19	0.2825
SUBT_ALCOHOL_VIOL	1.37	0.0063
VH_MAINT_VIOL	0.01	0.7779
HM_FlAG	-0.07	0.6959
Hourly_wage	-0.17	<.0001
Number of Observations Read	110,239	
Number of Observations Used	109,596	

Response Profile		
Ordered Value	**Crash**	**Total Frequency**
1	1	501
2	0	109095
Probability modeled is Crash='1'.		

The dependent variable is log(odds) of a crash, 1 for a crash, and 0 otherwise. Observations are at the incident level. Most estimated parameters of BASICs are not statistically significant, except for unsafe driving violation and controlled substances/alcohol violations. This is inconsistent with the findings of the CSA panel in 2017. Moreover, the parameter of the hourly wage is negative and statistically significant at the 1% level. Signs are also aligned with our expectations as we expect most of them to be positive. Hazmat drivers usually have more training. Thus, the sign is negative. Hourly wage also has a negative sign of crashes, which is consistent with the findings in Takahiko Kudo and Michael H. Belzer (2019). Driver fitness violation also has a negative sign because if a driver can get his license renewed due to health conditions, which will lead the trucker to drive less in exchange for health. Controlled substances/alcohol violations add the risk of a crash, and the sign expected to be positive. Since the three out of seven parameters are statistically significant in the logistic regression, we can transfer them into the probability function of each as below:

$$Prob_i = \frac{e^{(-1.87+0.22*\text{UNSAFE\_VIOL}+1.37*\text{Subt\_Alcohol\_Viol}-0.17*\text{Hourly\_wage})}}{1+e^{(-1.87+0.22*\text{UNSAFE\_VIOL}+1.37*\text{Subt\_Alcohol\_Viol}-0.17*\text{Hourly\_wage})}}$$

Notice that we dropped insignificant BASICs because their parameters are not statistically significant from zero.

Furthermore, we use this probability function and estimated parameters in 2017 to predict each vehicle's marginal probability of a crash in 2018, using 29,411 observed data in MCMIS. Then reconcile the estimates and compare them to the deterministic data in the MCMIS.

For economic costs, according to Tim Harmon, Geni Bahar and Frank Gross (2018), the comprehensive crash unit cost in 2010 dollars is $655,000 with severity level A, which represents suspected serious injury and fails between fatal injury and suspected minor injury. We use this recently estimated amount as a proxy for our per-unit economic cost, and thus the probability of a crash for each vehicle times unit cost of a crash becomes the expected cost per crash. For each carrier, the probability is the sum of each vehicle's probability.

Further, we rank all intrastate property carriers into five groups based on each carrier's probability of crashes, where 0 means the lowest risk, and 4 means the highest risk.

Table Summary of Risk Tiers

Rank	Intrastate Carriers	Crashes	Fatalities	Injuries	Warning Letters	Sum of Firm_Cost	Average of Firm_prob
0	5,981	250	14	262	153	12,287,160	0.31%
1	5,409	401	48	542	251	16,604,183	0.47%
2	6,211	588	55	767	308	30,026,653	0.74%
3	5,873	729	59	853	374	51,070,383	1.33%
4	5,937	2,763	255	3,180	669	183,553,875	4.72%
Grand Total	29,411	4,731	431	5,604	1,755	293,542,253	

This table shows the summary of each rank/risk tier, the number of crashes, fatalities, and injuries are increasing along the risk tiers. Carriers in Rank 4, the riskiest tier in our category for all intrastate carriers, have a much higher probability of a crash compared to others, resulting in an expected economic cost of $183 million (in 2016 dollars) to society for all Rank 4 carriers in our sample.

The warning letters column shows our estimated number of warning letters that could be sent to the carriers in 2018 since that is not publicly available in the MCMIS. Hence, we decide to replicate FCMSA's methodology and do our simulation, and we will discuss more details next.

FMCSA Crash Indicator

FMCSA uses this indicator to measure the historical pattern of crash involvement, including frequency and severity, while restricting to reportable crashes. A reportable crash means a crash involving at least one fatality, one injury requiring transportation to a medical facility, or one vehicle towed from the scene.

According to Panel on the Review of the Compliance Safety and Accountability, Committee on National Statistics and Transportation Research Board (2017), the formula is:

$$\text{Crash Indicator Measure} = \frac{\text{Total of time and severity weighted crashes}}{\text{Average PUs} \times \text{Utilization Factor}}$$

Where

Time and severity weights are available in the MCMIS dataset, given by the experts

PU means power units

Utilization factor is for adjusting carrier sizes

Table IV.6.1 exhibits the calculation of the utilization factor. Small interstate carries will get more likely to get a value less than 1, which translates to a larger crash indicator measure value.

Table 0.1 Utilization factors

Combination Segment	
Vehicle Miles Traveled (VMT) per Average Power Unit (PU)	**Utilization Factor**
< 80,000	1
80,000–160,000	$1 + \frac{VMT\ per\ Average\ PU - 80{,}000}{133{,}333}$
160,000–200,000	
> 200,000	1
No Recent VMT Information	1

In our simulation, the crash indicator has a range from 0.001653 to 88. Also, we calculate the percentile and get the following distribution:

Table 0.2 Estimated Percentile

P_50	P_60	**P_65**	P_70	P_75	P_80	P_85	P_90	P_95
0.55	0.90	**1.176**	1.50	2.00	2.66	3.86	5.60	10.00

According to the appendix in Panel on the Review of the Compliance Safety and Accountability, Committee on National Statistics and Transportation Research Board (2017), the intervention thresholds for Crash Indicator is 65% for general carriers. Therefore, we decide to use 1.176 as the threshold in our simulation. In other words, if any carrier in any month in 2018 has a crash indicator value that is greater than 1.176, then that carrier will receive a warning letter. In table 6.5.1, we see the number of letters increases along with the risk tiers in general, but the pace is different. Especially in Tier 4, the number of crashes is almost 4 times higher than that in Tier 3 while the number of letters is just doubled, which implies the current crash indicator fails to define and capture high-risk carriers. Meanwhile, FMCSA may consider lowering the threshold from 65% to 60% to be able to cover the Tier 3 group. The current crash indicator formula is based on subjective severity weights and compromise for firm sizes. From the function, we can infer that if a carrier purchases more power units, it receives "credits" for crashes since the denominator gets larger. It is opposite to our economic view of crashes, in which every crash creates externality to society.

Meanwhile, a large firm with many drivers and truckers does not necessarily associate with more crashes, because that firm can increase compensation to lower the risk of crashes, as we have tested and confirmed the negative relationship between the crash and hourly wage in the previous chapters.

Also, it is feasible because large firms have the economy of scale on reducing operating costs, while smaller firms may not have such advantages due to the size and market competition. Therefore, the current measurement may not be truly fair to all carriers, and we think it is essential to promote equity and efficiency from a regulator's perspective.

Table IV.6.3 Top 20 Risky Firms by Estimated Probability of Crashes

Top20	DOT_NUMBER	Firm_prob	Driver_prob	Rank	Crashes	Fatalities	Injuries	Letters
1	1589315	156.89%	0.223%	4	51	0	19	0
2	27641	245.86%	0.211%	4	36	0	42	0
3	813366	110.64%	0.453%	4	28	0	28	0
4	1197391	0.60%	0.001%	2	26	5	20	0
5	2588752	22.94%	0.024%	4	19	2	22	0
6	806301	18.14%	0.125%	4	18	3	17	0
7	2657958	68.58%	0.114%	4	16	3	19	0
8	1003451	46.33%	0.113%	4	14	0	11	0
9	723015	14.88%	0.038%	4	11	0	11	0
10	830501	54.01%	0.260%	4	11	0	5	0
11	565571	33.01%	0.375%	4	10	0	14	0
12	849101	11.14%	0.014%	4	10	3	16	0
13	970762	108.39%	0.473%	4	10	0	8	0
14	2808261	7.36%	0.008%	4	10	0	12	0
15	291818	3.26%	0.007%	4	9	0	9	0
16	424011	29.68%	0.149%	4	9	0	15	0
17	827166	18.61%	0.039%	4	9	3	0	0
18	83908	88.57%	0.338%	4	8	0	14	0
19	685979	118.86%	0.849%	4	8	2	8	0
20	818879	17.90%	0.058%	4	8	0	0	0

Table IV.6.3 shows the top 20 intrastate carriers by the number of crashes in 2018, and those carriers are not necessarily the top 20 largest carriers. Notice that letters fail to capture these firms mainly due to the firm size, as we can interpret from low the per driver probability.

On the contrary, our rank captures these risky carriers by using the estimated firm's probability for 2018, with one outlier. Therefore, the comparison suggests our method is less biased than the crash indicator method.

Policy Implication and Conclusion

Table IV.7.1 shows the correlation coefficients at the carrier level, more specifically intra-state property carriers. The estimated coefficients are all statistically significant at the 1% level. The firm's probability has a higher correlation than warning letters have, while the correlation between these two is low.

Table IV.7.1 Correlations

Pearson Correlation Coefficients (OBS=29411)						
	Firm_prob	**Rank**	**Crashes**	**Fatalities**	**Injuries**	**Letters**
Firm_prob	1	0.38	**0.58**	0.08	0.38	0.05
		<.0001	<.0001	<.0001	<.0001	<.0001
Letters	0.05	0.11	**0.36**	0.16	0.38	1
	<.0001	<.0001	<.0001	<.0001	<.0001	
Rank	0.38	1	**0.18**	0.05	0.13	0.11
	<.0001		<.0001	<.0001	<.0001	<.0001

That suggests these two are different approaches, while in the current sample, our paper's probability method shows more power of prediction than the FMCSA's crash indicator one, ours shows 61% more linear correlations than the warning letter one. In other words, with limited resources, our statistical model shows reasonable predictability, and it will be an excellent complement to the existing FMCSA metrics to improve the efficiency of governance and enforcement since the implementation cost is low as no additional variable nor structure change needed. Besides, the policymakers should emphasize rank 3-4 carriers in our model because the economic costs of those tiers are much higher than the others and consider lowering the exiting the current 65% threshold to 60% to be able to cover rank 3 carriers.

To wrap up, in this chapter, we use the public data and innovative bottom-up approach to estimate the intra-state property carrier's marginal probability of crashes. More specifically, we build a combined dataset from the BASIC violations, the OES wage and the MCMIS crashes in 2017. Then, we run a logistic regression to get significant parameters for predicting the log(odds) of a crash, in which Hourly wage as a proxy for compensation, showing a strong power of prediction: the higher wage rates, the lower the odds. Using linear transformation, we calculate the probability of a crash at the individual vehicle level in 2018 and then aggregate the individual probability of a crash to a joint one at the firm level for each intrastate carrier in our sample. Since the crashes data in 2018 are known in our full dataset, we can compare our estimated results to actual one. Pearson's correlation coefficient shows a value of 0.58, which is also statistically significant at the 1% level, suggesting a strong positive linear relationship between our estimated crashes and the actual ones.

Meanwhile, since the FMCSA's crash indicator is not available to the public, we simulate the FMCSA's crash indicator according to the FMCSA's methodology and find our proposed approach exhibits a 61% higher linear correlation than the FMCSA's. Also, our model is less biased toward large carriers. Consequently, we recommend FMCSA to use our proposed statistical method as a complement to the existing tools. Furthermore, we Besides, we estimate the economic costs by risk Tier/Rank, in our worst tier (Rank 4), the estimated economic cost to society is about $183 million (in 2016 dollars) for all Rank 4 carriers in our sample. Thus, we recommend FMCSA to allocate more resources on the high-risk groups, suggesting a more strict warning letter policy, more on-site inspections, and higher fines.

Chapter 5 CONCLUSION

This dissertation explores the relationship between FMCSA violations, earnings, and safety in three main chapters. In these three chapters we used the latest MCMIS data and implemented different statistical models to test the linkage between FMCSA BASIC violations and crashes in Chapter 2; validated the importance of economic factors to drivers' safety and estimated the marginal impact (elasticities) in Chapter 3; and proposed our alternative wage method to improve the current safety measurement in Chapter 4. This research follows the theoretical framework created by Belzer et al. (2002) and aims to answer the National Academy of Science, Engineering, Medicine's call for more analysis in this area. Our sample period covers from 2015 to 2018, and our focused group is intrastate property carriers in the U.S.

In Chapter 2, "HOS Compliance Violation and Crashes," we use cross-sectional Poisson and Negative Binomial models to test the linkage and causality between crashes and BASIC violations for the intrastate property-carrying sector in 2018, with a focus on hours of service (HOS) violations. According to our estimated results, not all BASIC violations are predictive of crashes; the parameters of driver fitness and controlled substance are not statistically significant at the 10% level. This finding is consistent with the one in Panel 2017 (Panel on the Review of the Compliance Safety and Accountability, Committee on National Statistics and Transportation Research Board, 2017). The coefficient of HOS violations is positive and statistically significant at the 1% level, meaning that more HOS violations correlate to more crashes on an annual basis. Furthermore, we use the Vector Autoregressive Model to simulate a typical intrastate carrier's impact and reaction to violations. The impulse response figure shows a favorable response of FMCSA-CVSA-state-police-issued violations on reducing the total number of crashes in the short run, which lasts about 8 months on average; the peak of reduction happens in the first two months after a HOS violations shock.

Moreover, the hourly wage indicates a favorable and robust impact on crashes, which is aligned with the results in other recent studies, and this raised our interest that earnings may be a main driving force to driver's safety. However, the current study is restricted to cross-sectional analysis in 2018, in which we assume intrastate carriers are homogeneous due to high market competition. In the following chapter, we will expand our sample period back to 2015 and take a longitudinal approach to validate the current findings further.

In Chapter 3, "Compensation and Safety – a Longitudinal Study," we mainly focus on the relationship between compensation and crashes. First, we validate the relationship between compensation and safety in Chapter 2 by implementing a longitudinal analysis covering a sample period from 2015 to 2018. Our pooled Negative Binomial model and Poisson Random Effects model shows our OES hourly wage is the most consistent and significant influence on crashes. We get the wage dataset from the Occupational Employment Statistics (OES) Survey by state and occupation, and the population data from the U.S. Census Bureau. OES provides an update on the median wage of each occupation in the US in May each year, which also includes a wide range of classification for a single industry. In this study, it is most Relevant to look at truck transportation (NAICS 484000), and we narrow down to "Heavy and Tractor-Trailer

Truck Drivers" (OCC 53-3032). Furthermore, we choose the median hourly pay of each state as our wage variable since we believe the wage of intrastate carriers will not be materially different from each other due to competition and high turnover in the market, while the hourly rates may differ across states due to the cost of living. Based on our estimated elasticities, at the mean, a 1% higher hourly pay rate correlates to 1.8% fewer crashes over 2015-2018. In 2018, the mid pay group had an elasticity -4.9, which is more elastic than the high pay group (20% above average) with an elasticity of -3.9. The low pay group (20% below average) has an inelastic wage-crash elasticity, so a marginal increase in hourly wage is not strong enough to incentivize safe driving for the low pay group. In other words, it is more cost-effective for mid pay carriers to offer a compensation raise because those truck drivers are more sensitive to a difference in hourly wage, trading for crashes.

One could argue the OES hourly wages are at the state level, so this variable is capturing the impact of state wealth instead of driver's wage. We test a model with state-level GDP per capita, replacing the hourly wage. The results show a negative sign and strong statistical significance. However, the elasticity is -1.32 for 2018 means that GDP per capita as proxy for state wealth is essential, but truckers are more sensitive to the change in hourly wage than state wealth in general. In other words, truck drivers' responsiveness to higher wages is significant, but offset by the state wealth effect. Truck drivers who work in wealthier states are safer than those who work in less wealthy states, but the dominant effect is the influence of truck driver wages on safety. Higher paid truck drivers are safer, controlling for state GDP. Meanwhile, from a regulator's perspective, the results of this study suggest that FMCSA should consider adding a firm's hourly wage to its MCs 150 file and use it as the 900th safety measurement indictor to improve the efficiency of oversights and enforcement. In other words, though FMCSA should keep their current enforcement strategy (enforce on the BASICS while targeting the carriers they think are unsafe), they could obtain a more robust safety outcome by tracking driver pay (as the 2017 NAS report recommends) and take carrier pay into effect in their evaluation of safety effectiveness (Panel on the Review of the Compliance Safety and Accountability, Committee on National Statistics and Transportation Research Board, 2017).

In Chapter 4, "Safety Measurement and Economic Impact," we use the public data and an innovative bottom-up approach to estimate the intrastate property carrier's marginal probability of crashes. More specifically, we build a combined dataset of the BASIC violations, the OES wage, and crashes in 2017. Then, we run a logistic regression at the vehicle level, since vehicle identification number (VIN) is available in the MCMIS dataset to estimate parameters and collect significant ones to predict the log(odds) of a crash. Hourly wage serves as a proxy for earnings, which shows a reliable power of prediction: the higher the wage rates, the lower the odds. Using linear transformation on the log(odds) and violations in 2018, we then calculate the probability of a crash at the individual vehicle level in 2018. Since the joint probability is the sum of each vehicle's probability, we aggregate the individual probability of a crash to the firm level for each intrastate carrier in our sample, matching VINs with DOT numbers.

Furthermore, the carrier level crash data in 2018 are known in our full dataset so that we can compare our estimated carriers' probabilities to the actual ones. Pearson's correlation coefficient shows a value of 0.58 between our estimated probabilities and actual crashes, which is also statistically significant at the 1% level, suggesting a strong positive linear relationship between our estimated probabilities and real crashes; the higher probabilities mean more crashes. Besides, currently, FMCSA uses its crash indicator to screen highly risky carriers, but this indicator is not publically available. More specifically, the MCMIS dataset does not tell when FMCSA has sent a warning letter to the carrier (the letter that they issue if the carrier has dropped below 65% of all carriers in BASICS). For them, the issuance of that warning letter is an important event. So two steps may be taken here. In the first step, the carrier gets a violation (one or more), and at the second step, the FMCSA sends them a warning letter if the carrier's BASIC summative score balls below 65%.

Hence, we simulate the FMCSA's crash indicator according to the FMCSA's methodology, and compare it with ours and find our proposed approach exhibits a 61% higher linear correlation than the FMCSA's. Consequently, we recommend FMCSA to use our proposed statistical method as a complement to the existing tools. Furthermore, we use the estimated probabilities to divide carriers into 5 risk tiers, 0-4 from lower risks to high risks. We believe FMCSA can utilize this method to detect high risky carriers using objective measures and allocate more resources to the group and thus promote economic efficiency and effectiveness.

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ABSTRACT

EMPIRICAL STUDY OF BASIC VIOLATIONS, PAY INCENTIVES, AND SAFETY: EVIDENCE FROM U.S. INTRASTATE CARRIERS

by

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Truck drivers are under financial pressure due to inadequacy in their compensation. Thus, they have strong incentives to work more legally or illegally in pursuing a higher income, which leads to fatigue and HOS violations and ultimately causes crashes. On the other hand, FMCSA oversees the motor carrier's safety performance and tries to improve the current safety measurement since everyone pays a share of the economic costs due to the externality. This dissertation aims to explore the complex relationship between BASICs violations, pay incentives and crashes, to raise the importance of economic impact on carrier's safety, and to test the effectiveness of the current FMCSA crash measurement and provide alternative statistical methods to improve efficiency and effectiveness of the enforcement.

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