

# Compliance, Safety, Accountability: Analyzing the Relationship of Scores to Crash Risk

October 2012



Prepared by the American Transportation Research Institute



**Compliance, Safety, Accountability:  
Analyzing the Relationship of Scores to Crash Risk**

October 2012

Micah D. Lueck  
Research Associate  
American Transportation Research Institute  
Saint Paul, MN



**950 N. Glebe Road, Suite 210  
Arlington, Virginia 22203  
[www.atri-online.org](http://www.atri-online.org)**

## ATRI BOARD OF DIRECTORS

**Mr. Steve Williams**  
**Chairman of the ATRI Board**  
Chairman & CEO  
Maverick USA, Inc.  
Little Rock, AR

**Mr. Michael S. Card**  
President  
Combined Transport, Inc.  
Central Point, OR

**Mr. Edward Crowell**  
President & CEO  
Georgia Motor Trucking Association  
Atlanta, GA

**Mr. Rich Freeland**  
President – Engine Business  
Cummins Inc.  
Columbus, IN

**Mr. Hugh H. Fugleberg**  
President & COO  
Great West Casualty Company  
South Sioux City, NE

**Mr. Jack Holmes**  
President  
UPS Freight  
Richmond, VA

**Mr. Ludvik F. Koci**  
Director  
Penske Transportation Components  
Bloomfield Hills, MI

**Mr. Chris Lofgren**  
President & CEO  
Schneider National, Inc.  
Green Bay, WI

**Mr. William J. Logue**  
President & CEO  
FedEx Freight  
Memphis, TN

**Ms. Judy McReynolds**  
President & CEO  
Arkansas Best Corporation  
Fort Smith, AR

**Mr. Jeffrey J. McCaig**  
President & CEO  
Trimac Transportation, Inc.  
Houston, TX

**Mr. Gregory L. Owen**  
Head Coach & CEO  
Ability/ Tri-Modal Transportation  
Services  
Carson, CA

**Mr. Douglas W. Stotlar**  
President & CEO  
Con-way Inc.  
Ann Arbor, MI

**Ms. Rebecca M. Brewster**  
President & COO  
American Transportation Research  
Institute  
Atlanta, GA

**Honorable Bill Graves**  
President & CEO  
American Trucking Associations  
Arlington, VA

## ATRI RESEARCH ADVISORY COMMITTEE

**Mr. Philip L. Byrd, Sr., RAC Chairman**  
President & CEO  
Bulldog Hiway Express

**Ms. Kendra Adams**  
Executive Director  
New York State Motor Truck Association

**Dr. Teresa M. Adams**  
Director of CFIRE  
University of Wisconsin

**Ms. Susan Alt**  
VP, Industry Relations and Public Affairs  
Volvo Group

**Ms. Cheryl Bynum**  
Manager, SmartWay Transport Partnership  
U.S. Environmental Protection Agency

**Mr. LaMont Byrd**  
Director, Safety & Health Department  
International Brotherhood of Teamsters

**Mr. Terry Croslow**  
Chief Financial Officer  
Bestway Express, Inc.

**Mr. Ted Dahlburg**  
Manager, Office of Freight Planning  
Delaware Valley Regional Planning  
Commission

**Mr. Tom DiSalvi**  
Director of Loss Prevention  
Schneider National, Inc.

**Mr. Chad England**  
Chief Operating Officer  
C.R. England, Inc.

**Mr. John Flanagan**  
Manager, Quality, Safety & Fleet Services  
Stevens Van Lines

**Mr. Tom Flies**  
Senior Director,  
Product Management  
Qualcomm

**Mr. Bryan Foe**  
Vice President, Transportation  
C.H. Robinson Worldwide

**Mr. David Foster**  
Vice President of Fleet Services  
Southeastern Freight Lines

**Ms. Patti Gillette**  
Safety Director  
Colorado Motor Carriers Association

**Mr. John Hancock**  
Director  
Prime, Inc.

**Mr. Steve A. Keppler**  
Executive Director  
Commercial Vehicle Safety Alliance

**Mr. Alan Korn**  
Chief Engineer Apps & Customer Support  
Meritor Wabco

**Ms. Jennifer Morrison**  
Vehicle Factors Engineer  
National Transportation Safety Board

**Mr. Dean Newell**  
Vice President, Safety  
Maverick USA, Inc.

**Mr. Steve L. Niswander**  
VP, Safety Policy & Regulatory Relations  
Groendyke Transport, Inc.

**Mr. Deane H. Sager**  
Director-Transportation Industry Practices  
The Northland Group

**Mr. Brett A. Sant**  
VP, Safety & Risk Management  
Knight Transportation, Inc.

**Mr. Jim Schultz**  
ITS Program Manager  
Michigan Department of Transportation

**Ms. Nanci Tellam**  
Group Director, Environmental Services &  
Sustainability  
Ryder System, Inc.

**Ms. Tom Weakley**  
Director of Operations  
Owner-Operator Independent Drivers  
Association Foundation

**Mr. Scott Wombold**  
Vice President, National Accounts & Wholesale  
Fuel  
Pilot Travel Centers

**Mr. Greer Woodruff**  
Senior Vice President of Corporate Safety &  
Security  
J.B. Hunt Transport Services, Inc.

**TABLE OF CONTENTS**

**Table of Contents** ..... i

**List of Figures** ..... ii

**List of Tables** ..... iii

**List of Acronyms** ..... v

**Executive Summary** ..... vi

**Key Findings**..... xii

**1.0 Introduction** ..... 1

Previous Research: Initial Evaluation of CSA ..... 2

Research Since UMTRI’s CSA Evaluation ..... 4

Transforming Non-Normal Data..... 6

Count Data and Negative Binomial Regression..... 8

**2.0 Current Research Methodology** ..... 10

**3.0 Research Findings** ..... 11

Relationships Between Percentile Scores and Crash Rates ..... 13

Comparing Above vs. Below Threshold Carriers ..... 18

Available Data and Safety ..... 26

**4.0 Supplementary Analyses**..... 27

Quantity of SMS Data and Safety ..... 27

Quantity of Negative SMS Data and Safety ..... 29

Making Safety Inferences from CSA: Recommendations ..... 31

**5.0 Caveats** ..... 34

**6.0 Conclusion**..... 35

**References**..... 37

**Appendix A** ..... 38

**Appendix B** ..... 39

**LIST OF FIGURES**

**Figure ES1. Relationship Between Unsafe Driving Scores and Crash Rates ..... vii**

**Figure ES2. Relationship Between Driver Fitness Scores and Crash Rates ..... viii**

**Figure ES3. Relative Crash Risk by Proposed Safety Category ..... x**

**Figure 1. Scatter Plot of Unsafe Driving BASIC Scores and Crash Rates..... 5**

**Figure 2. Histogram of Residuals ..... 6**

**Figure 3. Normal P-P Plot of Residuals ..... 6**

**Figure 4. Histogram of Carrier Crash Rates (Per 100 Power Units)..... 7**

**Figure 5. Scatter Plot of Unsafe Driving BASIC Scores and Log-Transformed  
Crash Rates ..... 8**

**Figure 6. New Histogram of Residuals ..... 8**

**Figure 7. New P-P Plot of Residuals ..... 8**

**Figure 8. Relationship Between Unsafe Driving Scores and Crash Rates ..... 14**

**Figure 9. Relationship Between Vehicle Maintenance Scores and Crash Rates ... 15**

**Figure 10. Relationship Between Fatigued Driving Scores and Crash Rates ..... 15**

**Figure 11. Relationship Between Driver Fitness Scores and Crash Rates ..... 16**

**Figure 12. Relationship Between Controlled Substances and Alcohol Scores and  
Crash Rates ..... 17**

**Figure 13. Safety Differences Between Unsafe Driving Categories ..... 20**

**Figure 14. Safety Differences Between Vehicle Maintenance Categories ..... 21**

**Figure 15. Safety Differences Between Fatigued Driving Categories ..... 22**

**Figure 16. Safety Differences Between Controlled Substance/Alcohol Categories  
..... 23**

**Figure 17. Safety Differences Between Driver Fitness Categories ..... 24**

**Figure 18. Relative Crash Risk As Number of Scores or “Alerts” Increases ..... 30**

**Figure 19. Relative Crash Risk by Proposed Safety Category ..... 33**

**LIST OF TABLES**

**Table ES1. Relative Crash Risk Among Carriers Above Vs. Below Threshold..... ix**

**Table ES2. Empirically Determined Continuum of Safety Risk..... xi**

**Table 1. SMS Summer Release Schedule ..... 10**

**Table 2. Overview of Database Utilized by ATRI..... 11**

**Table 3. Breakdown of Carriers with At Least One Assigned BASIC Score ..... 12**

**Table 4. Negative Binomial Regression Model for Unsafe Driving ..... 13**

**Table 5. Negative Binomial Regression Model for Vehicle Maintenance ..... 14**

**Table 6. Negative Binomial Regression Model for Fatigued Driving ..... 15**

**Table 7. Negative Binomial Regression Model for Driver Fitness..... 16**

**Table 8. Negative Binomial Regression Model for Controlled Substances and Alcohol..... 17**

**Table 9. Description of Variables Entered into ATRI’s Unsafe Driving Model ..... 19**

**Table 10. Negative Binomial Regression Model for Differences in Crash Rates – Unsafe Driving..... 19**

**Table 11. Description of Variables Entered into ATRI’s Vehicle Maintenance Model ..... 20**

**Table 12. Negative Binomial Regression Model for Differences in Crash Rates – Vehicle Maintenance..... 21**

**Table 13. Description of Variables Entered into ATRI’s Fatigued Driving Model .. 21**

**Table 14. Negative Binomial Regression Model for Differences in Crash Rates – Fatigued Driving..... 22**

**Table 15. Description of Variables Entered into ATRI’s Substance/Alcohol Model ..... 22**

**Table 16. Negative Binomial Regression Model for Differences in Crash Rates – Substance/Alcohol..... 23**

**Table 17. Description of Variables Entered into ATRI’s Driver Fitness Model..... 24**

**Table 18. Negative Binomial Regression Model for Differences in Crash Rates – Driver Fitness ..... 24**

**Table 19. Absolute Crash Risk Compared to Carriers With Data But No “Alerts” 25**

**Table 20. Description of Variables Entered into ATRI’s Model for Number of BASIC Scores ..... 27**

<b>Table 21. Negative Binomial Regression Model for Number of BASIC Scores .....</b>	<b>28</b>
<b>Table 22. Description of Variables Entered into ATRI’s Model for Number of “Alerts” .....</b>	<b>29</b>
<b>Table 23. Negative Binomial Regression Model for Number of “Alerts” .....</b>	<b>30</b>
<b>Table 24. Description of Variables Entered into ATRI’s Model for Proposed Safety Categories.....</b>	<b>32</b>
<b>Table 25. Negative Binomial Regression Model for Proposed Safety Categories.</b>	<b>32</b>
<b>Table 26. Empirically Determined Continuum of Safety Risk.....</b>	<b>36</b>



## LIST OF ACRONYMS

ATRI	American Transportation Research Institute
BASIC	Behavior Analysis Safety Improvement Category
CMV	Commercial Motor Vehicle
CSA	Compliance, Safety, Accountability
FMCSA	Federal Motor Carrier Safety Administration
Hazmat	Hazardous Material
ISS	Inspection Selection System
MCMIS	Motor Carrier Management Information System
OLS	Ordinary Least Squares
PU	Power Unit
SMS	Safety Measurement System
UMTRI	University of Michigan Transportation Research Institute
WRI	Wireless Roadside Inspection

## **EXECUTIVE SUMMARY**

Since the national launch of the Federal Motor Carrier Safety Administration’s (FMCSA) Compliance, Safety, Accountability (CSA) initiative, a handful of studies have attempted to study the degree to which motor carrier safety scores are related to actual carrier crash involvement. While each study offered numerous insights, the American Transportation Research Institute (ATRI) sought to expand on previous findings by utilizing a more targeted statistical analysis to answer two related research questions:

- **RQ1:** Are percentile scores related to actual safety (i.e. crash involvement)?
- **RQ2:** Does CSA properly classify carriers according to crash risk (i.e. do carriers with “Alerts” have higher crash rates than carriers without “Alerts”)?

According to FMCSA, high percentile scores in a Behavior Analysis Safety Improvement Category (BASIC) indicate a lack of compliance and greater exposure to potential safety problems, including crash involvement. That is, as scores go up, it is expected that crash involvement will also increase. However, previous researchers searched for, and failed to find, clear linear relationships between BASIC percentile scores and carrier crash rates.

This study proposes that a simple correlational approach may simply be unable to detect the existence of a relationship due to the nature of the data under consideration.<sup>1</sup> Crashes are infrequent events, and therefore special tools are required to model their occurrence.<sup>2</sup> Relying on best practices in the field of statistics, ATRI’s analysis uses a rigorous statistical approach to provide a more accurate description of the relationship (or lack thereof) between BASIC scores and crash involvement.

ATRI analyzed Safety Measurement System (SMS) and crash data for a sample of 471,306 motor carriers with evidence of recent activity in the past 24 months.<sup>3</sup> Analyses focused on the five BASICs that are available to the general public.<sup>4</sup>

---

<sup>1</sup> Authors relied upon simple correlations and Ordinary Least Squares (OLS) regression. This type of parametric analysis is subject to numerous statistical assumptions, nearly all of which were violated, raising questions about the studies’ conclusions.

<sup>2</sup> Crash data follow a negative binomial distribution, as opposed to a normal bell-shaped distribution.

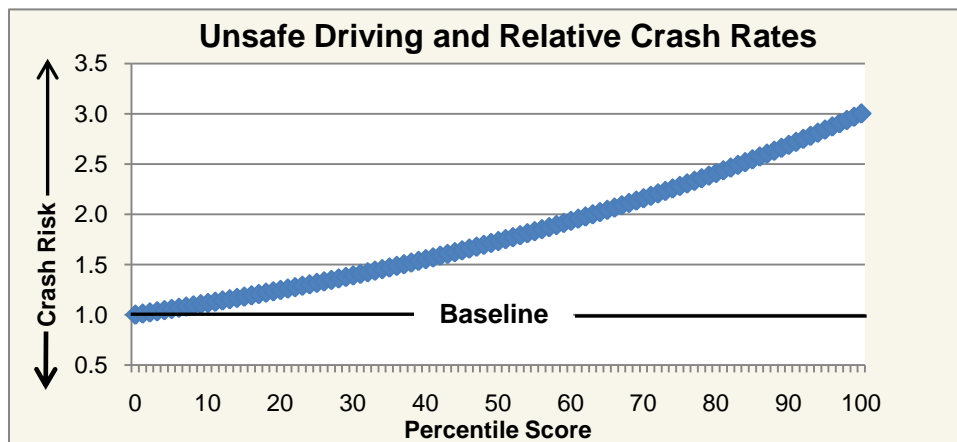
<sup>3</sup> This subset of carriers were selected from a sample of 772,281 registered interstate and intrastate hazardous material carriers.

<sup>4</sup> Unsafe Driving, Fatigued Driving, Driver Fitness, Vehicle Maintenance and Controlled Substances and Alcohol; the Crash Indicator and Cargo-Related BASICs are not public at the time of this publication.

---

### Relationships Between Percentile Scores and Crash Rates

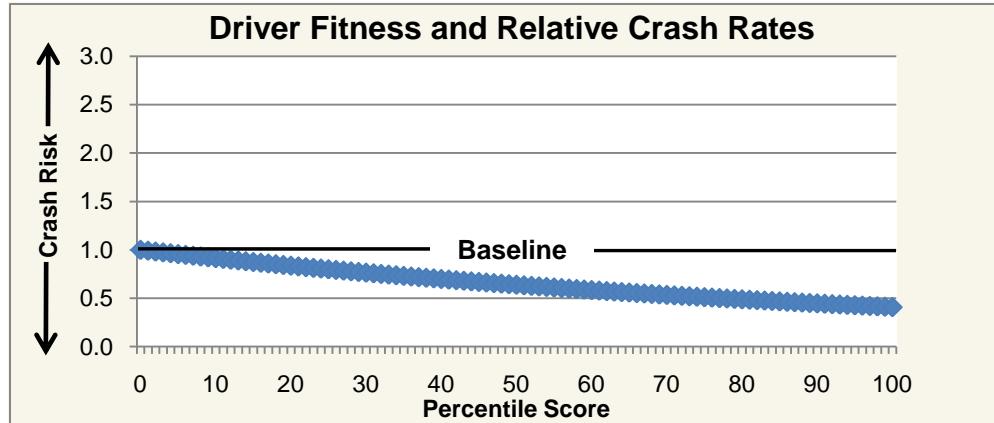
After explaining the rationale for choosing negative binomial regression modeling, ATRI’s first set of analyses searched for (non-linear) relationships between percentile scores and crash rates in each public BASIC. The analysis showed with high levels of confidence that BASIC scores are positively related to crashes in the Unsafe Driving, Fatigued Driving and Vehicle Maintenance BASICs, with the strongest relationship found for Unsafe Driving (depicted in Figure ES1).



**Figure ES1. Relationship Between Unsafe Driving Scores and Crash Rates**

The relationship demonstrates that, in the Unsafe Driving BASIC, as percentile scores increase, the risk of being involved in a crash also increases. For instance, a carrier with a score of 99 is roughly 3 times more likely, on average, to be involved in a crash compared to a carrier with a score of 0. The relationship to crash risk is similar, although somewhat weaker, for Fatigued Driving and Vehicle Maintenance, (i.e. a carrier with a score of 99 is 2.21 times more likely to be involved in a crash than a carrier with a score of 0 in each of those respective BASICs).

Meanwhile, ATRI found a *negative* relationship between the other two BASICs and crash involvement. That is, in the Driver Fitness and Controlled Substances and Alcohol BASICs, *higher* (i.e. worse) scores are associated with *lower* crash risks. The nature of these relationships is displayed in Figure ES2, where it is clear that the likelihood of being involved in a crash decreases as scores approach 100.



**Figure ES2. Relationship Between Driver Fitness Scores and Crash Rates**

In conclusion, ATRI’s first set of analyses provided mixed support for CSA. Percentile scores were positively related to actual safety (i.e. observed crash rates) for the Unsafe Driving, Fatigued Driving and Vehicle Maintenance BASICs. However, ATRI concluded that the SMS methodology for determining percentile scores is not calibrated correctly for the Controlled Substances and Alcohol or Driver Fitness BASICs. It is likely that FMCSA’s severity weighting methodology places too much weight on safety-irrelevant violations and too little weight on safety-critical violations in these two BASICs.

If FMCSA made the Agency’s severity weighting methodology public, ATRI could use a similar approach to that found in this paper to assess the accuracy of the severity weights applied by the SMS. In the meantime, 10,500 motor carriers (roughly 2% of all recently active carriers) have a CSA profile that publicly displays a flawed percentile score in the Driver Fitness and/or Controlled Substances and Alcohol BASIC. The scope of this misinformation, while clearly problematic, should be considered against the number of carriers for whom CSA does validly portray safety information (i.e. 89,829 carriers have a score in the Unsafe Driving, Fatigued Driving and/or Vehicle Maintenance BASICs).

**Comparing Above vs. Below Threshold Carriers**

Next, ATRI classified carriers into several groups determined by how much negative inspection data they possessed in each of the five BASICs. Of greatest interest was whether carriers with “Alerts” in each BASIC truly pose a higher safety risk than carriers with below threshold percentile scores.

The analysis revealed that carriers with an “Alert”<sup>5</sup> indeed demonstrated higher crash rates than carriers without “Alerts” in four of the five public BASICS: Unsafe Driving, Fatigued Driving, Vehicle Maintenance and Controlled Substances and Alcohol. In contrast, in the Driver Fitness BASIC, ATRI found that carriers with an “Alert” actually had *lower* crash rates than those without an “Alert” status.

Table ES1 reveals how much higher or lower crash rates are for carriers above threshold compared to carriers below threshold. Values greater than 1.0 imply a higher rate of crash involvement, whereas values less than 1.0 imply a lower risk of crashes. For instance, carriers with an “Alert” in Unsafe Driving, on average, have an expected crash rate 1.74 times higher than a carrier with an Unsafe Driving score below threshold. Conversely, carriers with an “Alert” in Driver Fitness, on average, have an expected crash rate .87 times *lower* than a carrier with a Driver Fitness score below threshold.

**Table ES1. Relative Crash Risk Among Carriers Above Vs. Below Threshold**

BASIC	Crash Risk
Unsafe Driving	1.74
Vehicle Maintenance	1.42
Fatigued Driving	1.34
Substance/Alcohol	1.32
Driver Fitness	0.87

In conclusion, “Alerts,” which incorporate carriers with Severe Violations in addition to high percentile scores, are reasonable safety indicators for four of the five BASICS. In the Driver Fitness BASIC, however, the SMS methodology for assigning carriers with an “Alert” status seems to target carriers with lower crash risk than those without an “Alert.” Again, it is suspected that the severity weighting methodology needs to be reevaluated to properly categorize high risk carriers into the Driver Fitness “Alert” group.

On the other hand, Appendix B explains why the Controlled Substances and Alcohol BASIC, which had a flawed percentile ranking system, still manages to properly classify the correct subset of high-risk carriers into the “Alert” group. Essentially, it is the Severe Violations in that BASIC that identify carriers with frequent safety incidents; these Severe Violations are therefore better indicators of crash risk than is the methodology for calculating Controlled Substances and Alcohol percentile scores.

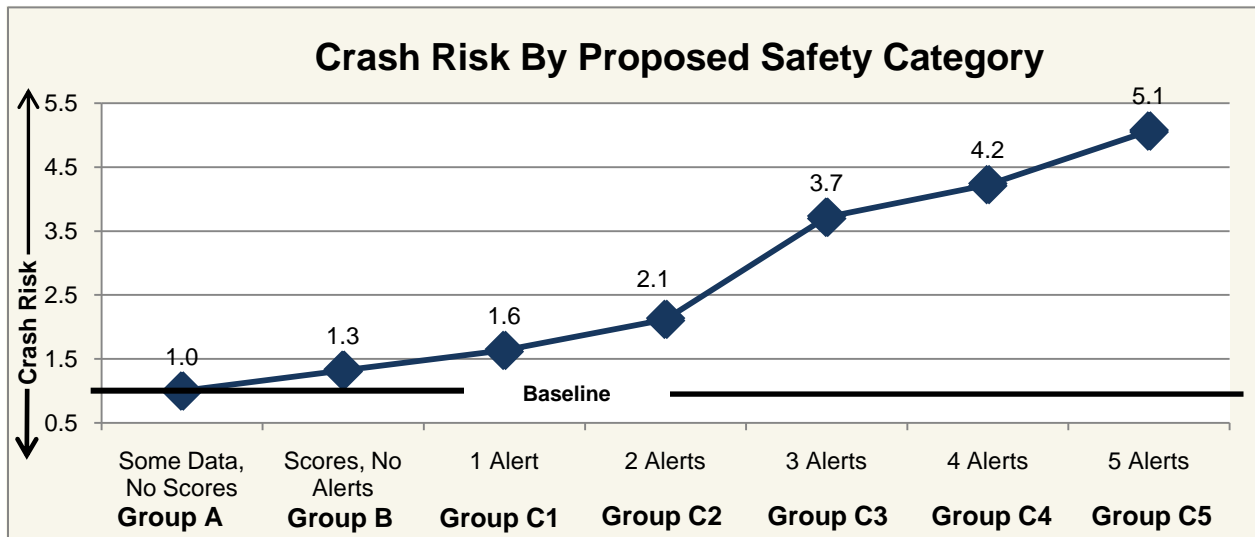
---

<sup>5</sup> Received as a result of possessing a percentile score above FMCSA’s cutoff and/or a Severe Violation.

**Supplementary Analyses**

Finally, ATRI performed several analyses using the SMS data to identify superior indicators of crash risk. These analyses showed, for instance, that the quantity of carrier data on file has a direct relationship to crash risk. Carriers with the lowest crash risk are those who have sufficient roadside inspection data to be assessed by the SMS, although not enough negative data (i.e. violations) to be assigned a score. From there, carriers with a score, even if it is below threshold, have increased odds of being in a crash.

Interestingly, as the number of assigned BASIC scores increase, crash rates continue to climb as well. The best indicator of crashes, however, is not how many BASIC scores a carrier has, but how many “Alerts” the carrier has. As seen in Figure ES3, carriers with an “Alert” in all five public BASICs have a crash rate roughly 5.1 times higher than a carrier with “Sufficient Data But No Score.”










**Figure ES3. Relative Crash Risk by Proposed Safety Category**

**Recommendations for an Alternative Scoring Mechanism**

In conclusion, as it is currently designed, CSA has a number of defects that still need to be addressed. While it may be helpful for FMCSA to continue using specific BASIC percentile scores for internal purposes, ATRI proposes several alternative scenarios for relaying safety and compliance information to the public. Since many stakeholders (e.g. shippers, insurers, litigants) assume CSA profiles reflect safety status, steps should be taken to provide to the public only information that can be reliably tied to safety.

ATRI found that percentile scores are flawed in two BASICs and even “Alerts” do not consistently identify the riskiest carriers within all five BASICs. The researchers proffer several new CSA approaches for categorizing carrier safety. One approach is reflected in Figure ES3, which could allow trucking stakeholders to better gauge fleet safety by classifying carriers into groups based on where they fall in the following chart (see Table ES2).

**Table ES2. Empirically Determined Continuum of Safety Risk**

Classification Group	Description	Level of Safety Risk	
		Low	High
Group A	Sufficient data in at least one BASIC, but no scores		
Group B	Scores in at least one BASIC, but no "Alerts"		
Group C-1	1 "Alert"		
Group C-2	2 "Alerts"		
Group C-3	3 "Alerts"		
Group C-4	4 "Alerts"		
Group C-5	5 "Alerts"		

## **KEY FINDINGS**

### **Impetus for Research:**

- Previous investigations of the link between CSA rankings and actual fleet safety did not adequately assess statistical assumptions.
- Negative binomial modeling is the preferred choice for analyzing crash data.

### **Relationships between Percentile Scores and Crash Rates:**

- Higher percentile scores in the Unsafe Driving, Fatigued Driving and Vehicle Maintenance BASICs reflect increased crash risk, as intended by the SMS.
  - 89,829 motor carriers have a score in one or more of these BASICs.
- In the Driver Fitness and Controlled Substances/Alcohol BASICs, carriers with higher percentile scores are involved in *fewer* accidents.
  - 10,500 motor carriers have a score in one or both of these BASICs.
- There is likely a problem with how the violations in the Driver Fitness and Controlled Substances/Alcohol BASICs are weighted.

### **Comparing Above vs. Below Threshold Carriers:**

- “Alerts” are more valid indicators of safety than raw percentile scores in the Controlled Substances and Alcohol BASIC (see Appendix B).
- Carriers with “Alerts” in the Unsafe Driving, Fatigued Driving, Vehicle Maintenance and Controlled Substances/Alcohol BASICs have significantly higher crash rates than carriers with “below threshold” scores in those BASICs.
- In the Driver Fitness BASIC, “Alerts” are assigned to carriers that have significantly *lower* crash rates than “below threshold” carriers.

### **Supplementary Analyses:**

- Having a percentile score (above or below threshold) is associated with higher crash rates than possessing no BASIC scores.
  - This is logical as percentile scores are based on negative roadside inspection data (i.e. violations).
- Similarly, carriers who have data populated in multiple BASICs have higher crash rates than carriers that are assigned only one BASIC score.
- However, the number of “Alerts” a carrier possesses is the most indicative of crash risk, with a greater number of “Alerts” signaling significantly higher risk.

### **Recommendations for an Alternative Scoring Mechanism:**

- New carrier classifications can be used to present more valid fleet safety profiles to the public (compared to the current CSA information that is publicly displayed).
- Carriers can also view the information to gauge safety impacts associated with possessing certain attributes (e.g. having two “Alerts” versus three “Alerts”).



## **1.0 INTRODUCTION**

In December 2010, the Federal Motor Carrier Safety Administration (FMCSA) initiated a new safety measurement program titled Compliance, Safety, Accountability (CSA). CSA relies upon a Safety Measurement System (SMS) which ranks motor carrier safety performance relative to other carriers that have similar levels of on-road exposure. These carrier SMS scores are issued in seven Behavior Analysis Safety Improvement Categories (BASICS): Unsafe Driving; Fatigued Driving; Driver Fitness; Controlled Substances/Alcohol; Vehicle Maintenance; Cargo-Related; and Crash Indicator. Scores in five of the seven BASICS are publicly available online at [www.ai.fmcsa.dot.gov/sms](http://www.ai.fmcsa.dot.gov/sms).<sup>6</sup>

As part of the SMS methodology, 24 months of crash, roadside inspection and enforcement case data are gathered from the Motor Carrier Management Information System (MCMIS) and sorted into the respective BASIC(s).<sup>7</sup> Roadside inspection violations are weighted according to their individual relationships to crash risk as well as according to how much time has elapsed since the event occurred, with more weight attributed to the most recent and severe safety-related events.<sup>8</sup> Once these raw data are sorted, normative scores from 0-100 are assigned to carriers for each individual BASIC, with lower scores indicating better performance relative to other carriers.

The overall purpose of CSA is to “improve large truck and bus safety to achieve a greater reduction in commercial motor vehicle (CMV) crashes, injuries and fatalities.”<sup>9</sup> And while a 2012 survey of motor carriers by the American Transportation Research Institute (ATRI) revealed that most fleets do not oppose CSA being used for enforcement purposes, it also showed that more than half of carriers oppose BASIC scores being publicized to other stakeholders who may interpret the scores as reflecting company safety performance.<sup>10</sup>

With that in mind, the research question of whether the FMCSA-assigned carrier BASIC scores truly relate to crash risk has taken center stage. Numerous researchers have attempted to answer the question; however, each approach has been associated with critical flaws that prevent a definitive conclusion from being drawn.

---

<sup>6</sup> Excluding the Cargo-Related and Crash Indicator BASICS

<sup>7</sup> John A. Volpe National Transportation Systems Center. (2012). *Safety Measurement System (SMS) Methodology, Version 2.2*. Washington, DC: Federal Motor Carrier Safety Administration. Available Online: <https://csa.fmcsa.dot.gov/Documents/SMSMethodology.pdf>

<sup>8</sup> John A. Volpe National Transportation Systems Center. (2009). *Comprehensive Safety Analysis 2010: Carrier Safety Measurement System Violation Severity Weights*. Washington, DC: Federal Motor Carrier Safety Administration. Available Online: <http://www.regulations.gov/#!documentDetail;D=FMCSA-2004-18898-0161>

<sup>9</sup> Federal Motor Carrier Safety Administration. *Compliance, Safety, Accountability (CSA)*. Available Online: <http://csa.fmcsa.dot.gov/default.aspx>

<sup>10</sup> American Transportation Research Institute. *Compliance, Safety, Accountability: Evaluating A New Safety Measurement System And Its Implications*. (Unpublished manuscript)

## **Previous Research: Initial Evaluation of CSA**

FMCSA contracted with the University of Michigan Transportation Research Institute (UMTRI) to complete an evaluation of CSA. In August 2011, UMTRI published a thorough report<sup>11</sup> evaluating many components of the program, including meaningful comparisons to SafeStat.<sup>12</sup> Key findings indicated that CSA was generally more cost-effective than SafeStat, while simultaneously better at targeting carriers, and identifying and correcting safety problems.

On the issue of whether the SMS validly rates carriers according to crash risk, UMTRI presented a range of analyses. Preliminary findings demonstrated that carriers that exceed any of the seven BASIC thresholds have higher crash rates, on average, than carriers who exceed no BASIC thresholds. However, further analyses began revealing certain problems inherent in the SMS.

First, the correlational analyses performed by UMTRI displayed only partial support for the idea that, as BASIC percentile scores increase (and therefore suggest greater safety concerns), so do actual crash rates. In five of the seven BASICs, a positive association was found, while the remaining two BASICs appeared to function differently. The Cargo-Related BASIC displayed a curvilinear relationship with crash rates, whereas the Driver Fitness BASIC was actually found to have a negative relationship to crashes, indicating that worse scores in that BASIC are associated with better crash outcomes.

Subsequently, the authors of the UMTRI report concluded their chapter on the associations between BASIC scores and crash rates with a more sophisticated analysis. The authors utilized negative binomial regression modeling, the approach that will be used in this paper, to evaluate differences in crash rates between three groups:

- (1) carriers with no percentile score;
- (2) carriers with a below threshold score; and
- (3) carriers with an above threshold score.<sup>13</sup>

Unfortunately, although the majority of stakeholders are presumably most interested in safety differences between above and below threshold carriers (i.e. Group 2 vs. 3), the authors chose to explain only the differences between above threshold carriers and those with insufficient data to generate a score (Group 1 vs. 3). However, an ATRI

---

<sup>11</sup> Green, P. E. & Blower, D. (2011). *Evaluation of the CSA 2010 Operational Model Test*. (Report No. FMCSA-RRA-11-019). Washington, DC: Federal Motor Carrier Safety Administration.

<sup>12</sup> SafeStat measured motor carrier safety performance and compliance prior to CSA

<sup>13</sup> The authors correctly omitted the Crash Indicator BASIC from the analysis, since crashes were the variable being predicted by the model

review of UMTRI's findings<sup>14</sup> also allows for a comparison of crash rates between below threshold carriers and those with insufficient data (Group 1 vs. 2). Interestingly, the UMTRI statistics revealed that carriers with *below* threshold scores in the Unsafe Driving, Fatigued Driving, Vehicle Maintenance and Cargo-Related BASICs also had higher crash rates than carriers with insufficient data in those BASICs.

The comparison of most value (i.e. above vs. below threshold) can only be performed manually, using the parameter estimates found in the table<sup>15</sup> and the following formula:  $e^{(b_3 - b_2)}$ . Had the UMTRI authors fully interpreted these findings from their negative binomial model, they would have revealed that the only BASICs where above threshold carriers had higher crash rates than carriers with below threshold BASICs are:

- **Unsafe Driving:** the crash rate for a carrier that exceeds the Unsafe Driving threshold is 1.83 times the rate of a carrier whose percentile score is below threshold (*statistically significant*)
- **Vehicle Maintenance:** the crash rate for a carrier that exceeds the Vehicle Maintenance threshold is 1.11 times the rate of a carrier whose percentile score is below threshold (*statistically significant*)
- **Fatigued Driving:** the crash rate for a carrier that exceeds the Fatigued Driving threshold is 1.05 times the rate of a carrier whose percentile score is below threshold (*likely not statistically significant*)
- **Controlled Substance/Alcohol:** the crash rate for a carrier that exceeds the Substance/Alcohol threshold is 1.03 times the rate of a carrier whose percentile score is below threshold (*likely not statistically significant*).

Conversely, according to UMTRI's statistical model, the two BASICs that displayed unexpected correlations earlier in the report again presented unusual problems:

- **Driver Fitness:** the crash rate for a carrier whose percentile score is below the Driver Fitness threshold is 1.18 times the rate of a carrier whose score exceeds the threshold (*statistically significant*)
- **Cargo-Related:** the crash rate for a carrier whose percentile score is below the Cargo-Related threshold is 1.10 times the rate of a carrier whose score exceeds the threshold (*likely statistically significant*).

Finally, in addition to the fact that UMTRI's analysis lacked explanations for the differences in crash rates between above and below threshold carriers, the data used in the study are now somewhat outdated. UMTRI's analysis relied upon carrier SMS scores calculated for February 2008 and crash data between February 2008 and July 2009. While these were reasonable and purposeful decisions, updated data are now available and deserve attention.

---

<sup>14</sup> Table 36, p. 47

<sup>15</sup> Table 36, p. 47

## **Research Since UMTRI's CSA Evaluation**

More recently, a series of independent analyses have been released with the general consensus that BASIC scores are weakly, or not at all, related to actual crash rates. Among the most notable of these studies are papers by Wells Fargo,<sup>16</sup> Transplace<sup>17</sup> and the University of Maryland.<sup>18</sup>

In addition to challenging the existence of an SMS-crash relationship, these studies raise a number of concerns questioning the general validity of the SMS. The various authors argue, and ATRI agrees, that the SMS suffers from selection bias, introducing systematic error into the measurement system. For instance, large carriers are much more likely to have one or more BASIC scores than small or midsized carriers, and are therefore overrepresented in the SMS. Nonetheless, FMCSA assumes this measurement program, although primarily based on large carriers, is suitable for all carriers (despite meaningful differences in operations between small and large firms).

Similarly, the authors correctly argue that the region of the country where a carrier runs the most miles introduces other artificial explanations for differences in BASIC scores. That is, there are meaningful discrepancies in both the sheer number of violations and the type of violations that are emphasized depending on where a roadside inspection is conducted. One paper states that just five states account for 45 percent of all Unsafe Driving violations.<sup>19</sup> Again, this raises a reasonable question of whether measured carriers are representative of all carriers, which has implications for whether trucking stakeholders can validly draw safety inferences from SMS scores.

Finally, in addition to pointing out issues with validity, the Wells Fargo, Transplace and Maryland researchers also question how reliable the assigned percentile scores are, particularly for small carriers. In statistics, scores that are based on few observations (e.g. less than 20 roadside inspections) are typically more prone to error and subject to change dramatically from additional data. As a result, spurious conclusions can be drawn if scores are not, in fact, reliably measured.

---

<sup>16</sup> Gallo, A. P. & Busche, M. CSA: Another look with similar conclusions. *Wells Fargo Securities Equity Research*. July 12, 2012.

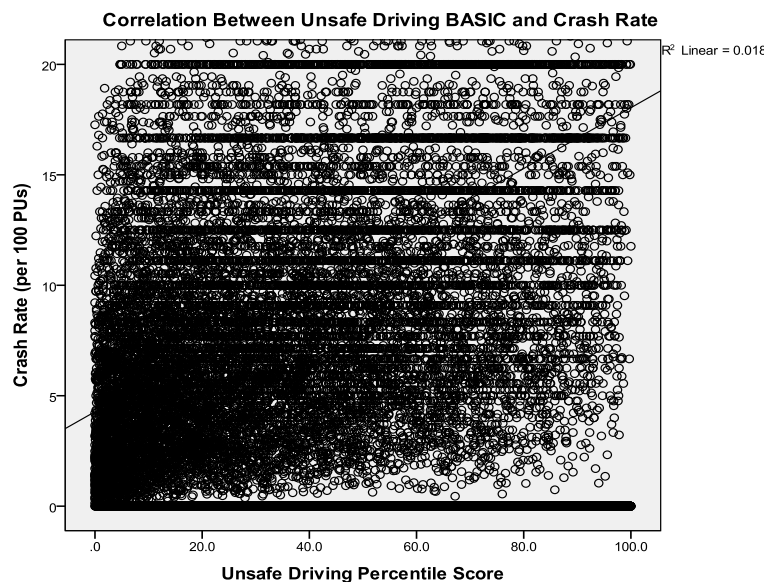
<sup>17</sup> Iyob, I. SMS BASIC scores are not valid predictors of crash frequency. *Alliance for Safe, Efficient and Competitive Truck Transportation*. June 25, 2012. Available Online: <http://asectt.blogspot.com/2012/06/sms-basic-scores-are-not-valid.html>

<sup>18</sup> Gimpel, J. Statistical issues in the safety measurement and inspection of motor carriers. *Alliance for Safe, Efficient and Competitive Truck Transportation*. July 10, 2012. Available Online: <http://asectt.blogspot.com/2012/07/news-brief-university-of-maryland-study.html>

<sup>19</sup> Gimpel, J. Statistical issues in the safety measurement and inspection of motor carriers. *Alliance for Safe, Efficient and Competitive Truck Transportation*. July 10, 2012. Available Online: <http://asectt.blogspot.com/2012/07/news-brief-university-of-maryland-study.html>

These critiques each deserve serious consideration from FMCSA. However, the purpose of this paper is not to examine issues of reliability and validity within the SMS, but to evaluate the statistical association between BASIC scores and crash rates as they currently stand. To that effect, ATRI will first conduct a comparative analysis of the statistical tools used by previous researchers and those utilized in this paper.

Unlike UMTRI, the Wells Fargo, Transplace and Maryland researchers used only a single analytical approach, which was to search for linear correlations in the data. Using the Unsafe Driving BASIC as an example, the scatter plots produced by the authors revealed little or no association between BASIC scores and crash rates, as seen in Figure 1 ( $r = .13$ ,  $p \leq .01$ ).



**Figure 1. Scatter Plot of Unsafe Driving BASIC Scores and Crash Rates**

The authors deduce from this that a clear cut association does not exist, supported by the chaotic scatter plot and the extremely low  $R^2$  value ( $R^2 = .02$ ), meaning that BASIC scores explain very little variance in crash exposure. One author further interprets the situation as follows:

“... the errors around the regression line indicate that the amount of variation in accident risk explained by the unsafe driving score...is modest at best. As Wells Fargo indicated, because it is intuitive that this relationship should be positive and clear-cut, there is either something wrong with the SMS measurement of unsafe driving, or something wrong with the sample of carriers in the MCMIS data.”<sup>20</sup>

<sup>20</sup> Gimpel, J. Statistical issues in the safety measurement and inspection of motor carriers. *Alliance for Safe, Efficient and Competitive Truck Transportation*. July 10, 2012. Available Online: <http://asectt.blogspot.com/2012/07/news-brief-university-of-maryland-study.html>

It is true that the absence of a clear relationship could mean that the two variables (carrier BASIC scores and crash rates) are truly unrelated or improperly measured; however, a third option is overlooked by the authors. Simply put, the failure to detect a relationship may be the result of choosing an incorrect statistical analysis. A primary duty of running statistical tests, and determining that relationships exist as specified in the model, involves checking statistical assumptions and model diagnostics. For Ordinary Least Squares (OLS) regression analyses (which include correlations and linear regressions), checking assumptions includes plotting the model’s error terms. The error terms should follow close to a normal distribution if the correct analysis is being applied for the variables under consideration.

In this case, both the histogram of residuals (i.e. error terms) and the normal P-P plot deviate strongly from what might be expected when using the appropriate statistical test (see Figures 2 and 3). Figure 2 should follow an approximately normally distributed bell curve, whereas the dark data points in Figure 3 should approximate the diagonal line. Clearly, neither of these assumptions holds, with Figure 2 revealing that the residuals are markedly positively skewed (i.e. most cases cluster on the left side of the figure and trail off to the right).

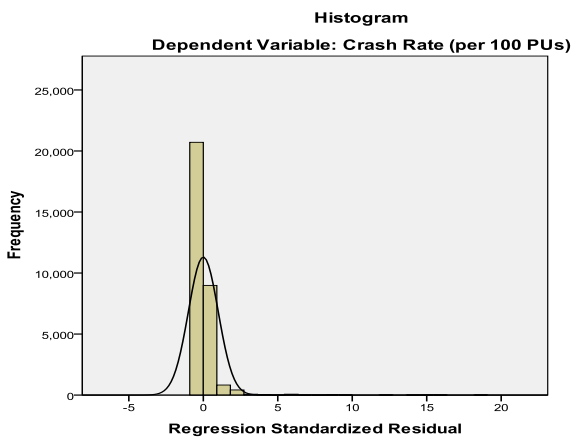


Figure 2. Histogram of Residuals

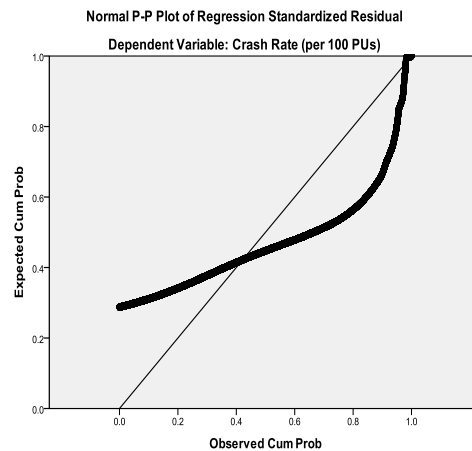
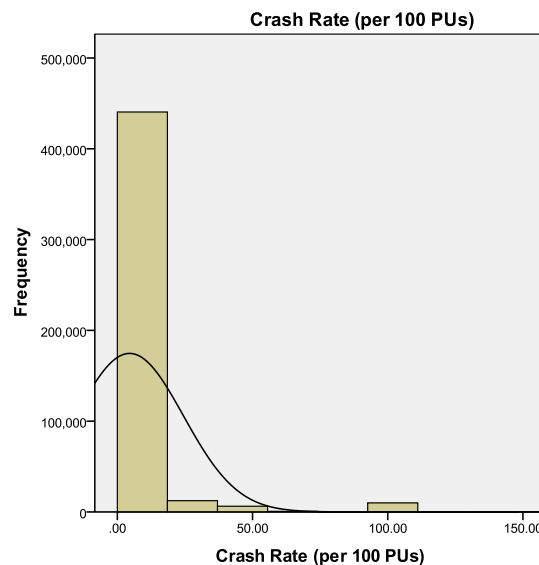


Figure 3. Normal P-P Plot of Residuals

**Transforming Non-Normal Data**

The strong deviations from normality discovered when checking OLS assumptions suggest that several assumptions were violated and the choice of analysis is therefore inappropriate for analyzing the relationship between carrier BASIC scores and crash rates. As a result, the lack of a relationship observed in the scatter plot (see Figure 1) is due to user error (i.e. selecting the incorrect type of analysis) and not necessarily because the two variables under investigation are truly unrelated.

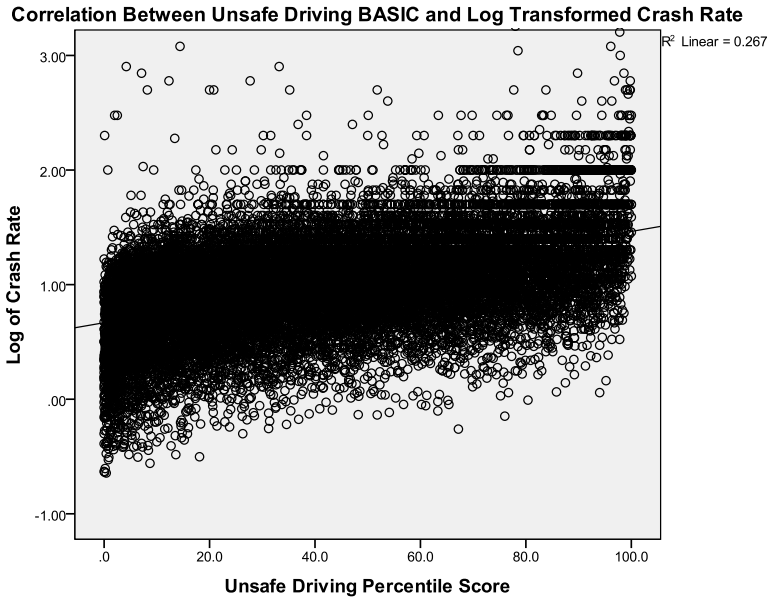
Since conclusions cannot be drawn from the simple linear regression used by the Wells Fargo, Transplace and Maryland authors, there are several alternative approaches available to answer the research question. Statisticians often choose to handle non-normally distributed data by transforming the problem variable(s). Typically, the histogram of residuals (Figure 2) closely follows the distribution of the dependent variable, in this case fleet crash rates per 100 power units (PUs). Plotting a histogram of carrier crash rates confirms that this is the variable that needs to be addressed (see Figure 4).



**Figure 4. Histogram of Carrier Crash Rates (Per 100 Power Units)**

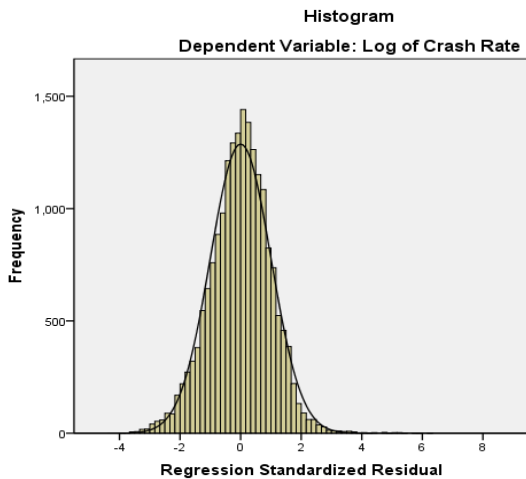
While absolute values for skewness and kurtosis should be less than or equal to 2.00, this variable has *Skewness* = 14.46 and *Kurtosis* = 737.19. Moreover, the variable displays tremendous overdispersion, a data issue that arises when the variance exceeds the mean ( $M = 4.53$ ;  $Variance = 396.69$ ). A common method for dealing with a variable such as this is to apply a transformation that normalizes the variable. For positively skewed variables, a log transformation is often the first option to test. In this case, log-transforming carrier crash rates improves the situation somewhat ( $M = 1.25$ ;  $Variance = 0.36$ ;  $Skewness = -1.00$ ;  $Kurtosis = 2.20$ ).

Regressing the log-transformed variable (rather than raw crash rate) on the Unsafe Driving BASIC score reveals a different conclusion concerning the presence of a relationship (see Figure 5). In fact, this analysis suggests a modest positive association, wherein observed crash rates become higher as BASIC scores increase ( $r = .52$ ,  $p \leq .01$ ). Furthermore,  $R^2$  indicates that the Unsafe Driving BASIC score explains a significant 26.7 percent of the variation in carrier crash rates.

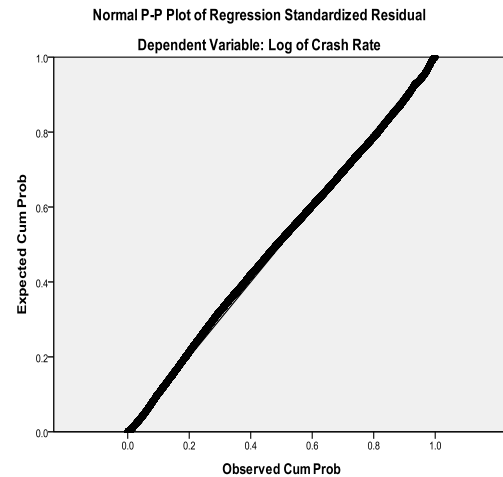


**Figure 5. Scatter Plot of Unsafe Driving BASIC Scores and Log-Transformed Crash Rates**

Finally, examining the assumptions of this analysis confirms that the previously discussed statistical assumptions are no longer violated by the model. That is, the histogram of the model’s predicted error terms (see Figure 6) almost perfectly fit a bell curve, and the P-P plot of residuals (see Figure 7) map to the expected diagonal line.



**Figure 6. New Histogram of Residuals**



**Figure 7. New P-P Plot of Residuals**

**Count Data and Negative Binomial Regression**

Nonetheless, although log-transforming variables is a common statistical practice that resolves many of the issues encountered by the simple correlational approach, it is still deemed insufficient by the author of this paper.



Principally, this is because crash data (the dependent variable under consideration) are considered *count* data, a statistical data type in which observations can take only non-negative integer values (e.g. 0, 1, 2, 3 ...). Specifically, the count data in this study are the number of crash occurrences a motor carrier experiences over a 24-month period.

As this paper has demonstrated, simple OLS regression (including raw correlations) are inappropriate in this context.<sup>21</sup> Further, data transformations (such as the log transformation used in the previous section) appear on the surface to be valid, but also have drawbacks. The main purpose of applying transformations is to correct for non-normality and/or heteroscedasticity<sup>22</sup> so that the sample data do not violate the assumptions of parametric statistics (e.g. OLS regression).

However, this approach is simply an adaptation of OLS, which may still produce biased, inefficient and inconsistent parameter estimates.<sup>23</sup> Thus, researchers have developed superior analyses intended specifically for count-type data, the most popular of which are Poisson regression and negative binomial regression.<sup>24</sup> Poisson models assume the mean and variance of the response variable are equal, which is known to be untrue in this case (i.e. the variance of crash events is more than 10 times larger than the mean). Negative binomial models, on the other hand, allow for an extra parameter to model this overdispersion, rather than restricting the mean and variance to be equal.

The negative binomial model has the following form:

$$\lambda_i = EXP(\beta X_i + \varepsilon_i)$$

where  $\lambda_i$  is the expected number of events per period

$\beta$  is a vector of parameters which will be estimated

$X_i$  is a vector of explanatory variables, and

$EXP(\varepsilon_i)$  is a gamma distributed error term with mean 1 and variance  $\alpha^2$ .

Since this analysis is based on the negative binomial distribution (rather than a normal distribution), it is not sensitive to the same types of statistical assumptions as OLS regression.

---

<sup>21</sup> Atkins, D. C. & Gallop, R. J. (2007). Rethinking how family researchers model infrequent outcomes: A tutorial on count regression and zero-inflated models. *Journal of Family Psychology*, 21(4), 726-735.

<sup>22</sup> Non-uniform error variance

<sup>23</sup> Long, J. S. (1997). *Regression models for categorical and limited dependent variables*. Thousand Oaks, CA: Sage Publications.

<sup>24</sup> These are known within the statistical community as Generalized Linear Models

## **2.0 CURRENT RESEARCH METHODOLOGY**

This paper relies upon statistical best practices for analyzing crash data (i.e. negative binomial modeling). Data used for these analyses were taken from three publicly available sources; the MCMIS crash file, carrier census file and carrier SMS file extracts.<sup>25</sup>

Census and SMS data were downloaded August 20, 2012, providing July 2012 data for the analysis (see Table 1 for FMCSA’s SMS summer release schedule).<sup>26,27</sup> At the same time, ATRI ordered a MCMIS crash file extract from FMCSA, which was current as of July 12, 2012. Since all crashes are required to be uploaded by the States within 3 months, this paper incorporates the 24 months of crash data entered in MCMIS between April 12, 2010 and April 11, 2012.<sup>28</sup>

**Table 1. SMS Summer Release Schedule**

<b>Release Month</b>	<b>Data Snapshot Date</b>	<b>Approximate Release Date</b>
July 2012	Friday, 06/22/2012	Week of 07/02/2012
August 2012	Friday, 07/27/2012	Week of 08/06/2012
September 2012	Friday, 08/24/2012	Week of 09/03/2012

Although data were available for interstate motor carriers, intrastate hazardous material (hazmat) carriers and intrastate non-hazmat carriers, the latter group of carriers was excluded from this study.<sup>29</sup> Additionally, the researchers made an effort to reduce the data file from 772,281 registered motor carriers to include only active carriers. The rationale for this was that non-active carriers would, by default, have zero crashes on record and therefore artificially lower carrier crash rates, biasing subsequent analyses. Therefore, the criteria used to establish recent carrier activity included only the 471,306 carriers possessing at least one of the following attributes:

- (1) a MCS-150 form that has been updated in the past two years;
- (2) one or more inspections or violations reported in the past two years; and/or
- (3) one or more crashes occurring in the past two years.

<sup>25</sup> The SMS data included only five of the seven BASICS, as data for the Cargo-Related and Crash Indicator BASICS are not available to the public.

<sup>26</sup> SMS results are updated monthly. A snapshot of the data is taken on the 3rd or 4th Friday of each month and then it takes approximately 10 days to process and validate the data. Once validated, the results are uploaded to the SMS Website.

<sup>27</sup> For a complete list of variables included in these files, please visit FMCSA’s CSA website: <http://ai.fmcsa.dot.gov/sms/Data/Downloads.aspx>

<sup>28</sup> The most recent 24 months of crash data that can be considered reliable.

<sup>29</sup> SMS data for intrastate non-hazmat carriers are handled on a state-by-state basis and differ meaningfully from the carriers subject to federal regulations (i.e. interstate and intrastate hazmat carriers).

### 3.0 RESEARCH FINDINGS

ATRI first ran some initial exploratory analyses to establish the validity of the dataset being utilized for this study. For instance, Table 2 was produced after cleaning the dataset, and the figures closely replicate those published by FMCSA;<sup>30</sup> nearly 500,000 carriers are considered active<sup>31</sup> and roughly 200,000 have sufficient inspection data to be assessed in at least one BASIC (i.e. combining the 109,837 carriers who have inspection data but no score and the 90,623 carriers with at least one assigned score). Also similar to the figures reported by FMCSA, approximately 54 percent of carriers with one or more assigned BASIC scores had at least one “Alert”<sup>32</sup> (N = 49,078).

**Table 2. Overview of Database Utilized by ATRI**

Carrier Category	Number of Carriers	Percentage of Recently Active Carriers	Number of Crashes in Database <sup>33</sup>	Percentage of Crashes in Database
Carriers with Recent Activity <sup>34</sup>	471,306	100%	162,455	100%
Carriers with Insufficient Data	270,846	57.5%	11,831	7.3%
Carriers with Some Data but No Scores	109,837	23.3%	17,212	10.6%
Carriers with At Least 1 BASIC Score	90,623	19.2%	133,412	82.1%

Several preliminary conclusions can be drawn from Table 2 by cross-referencing the percent of carriers in each category and the percent of crashes accounted for by that group. For instance, although carriers with “sufficient inspection data but no scores” and carriers with “at least one BASIC score” comprise similar proportions of the database (i.e. 23.3% and 19.2%), the latter group has almost eight times as many crashes as the former (i.e. 82.1% vs. 10.6% of all crashes). Meanwhile, carriers with “insufficient inspection data,” despite making up the majority (57.5%) of the database, account for an even smaller proportion of all crashes (i.e. 7.3%).

<sup>30</sup> Federal Motor Carrier Safety Administration. (2012). *Review of Wells Fargo Equity Research Report on Compliance, Safety, Accountability*. Available Online:

[http://www.cvsa.org/news/documents/2012/FMCSA%20Analysis%20of%20Wells%20Fargo%20Report%20re%20CSA%20-%20FMC-120124-006\).pdf](http://www.cvsa.org/news/documents/2012/FMCSA%20Analysis%20of%20Wells%20Fargo%20Report%20re%20CSA%20-%20FMC-120124-006).pdf)

<sup>31</sup> FMCSA cites 525,000 carriers as being recently active; however, the Agency uses additional criteria that were not available within the databases accessed as part of this study

<sup>32</sup> The term “Alert” will be used throughout this paper, with the acknowledgement that FMCSA no longer uses the term and instead uses the following symbol: ⚠

<sup>33</sup> Between April 12, 2010 – April 11, 2012

<sup>34</sup> Out of the 772,281 motor carriers in FMCSA’s SMS files (interstate and intra-state hazmat)

This suggests that the SMS is correctly targeting the carriers that account for most of the industry’s safety incidents. That is, the 270,846 carriers that are not assessed by the SMS are the least crash-involved group (i.e. “insufficient data” carriers). Similarly, the 109,837 carriers with “sufficient data but no scores” have limited crash exposure, whereas the carriers accounting for the largest share of crashes (82.1%) have already been assigned at least one BASIC score.

Within the group of carriers that have a score (and account for 82.1% of all crashes), however, the issue that arises is whether these carriers are assigned scores that reflect the degree of safety risk presented by each fleet. It appears on the surface as though simply possessing a score is associated with higher crash risk, perhaps regardless of whether a carrier is assigned an above or below threshold score. Of the roughly 90,000 carriers with a score, close to 55 percent have at least one BASIC above threshold while approximately 45 percent do not. Nonetheless, the share of crashes belonging to these two groups are almost perfectly reversed (i.e. the 55% of above threshold carriers are responsible for 43.1% of crashes while the 45% of below threshold carriers are responsible for 56.9% of the crashes in Table 3).

**Table 3. Breakdown of Carriers with At Least One Assigned BASIC Score**

Carrier Category	Number of Carriers	Percentage of Carriers with At Least 1 BASIC Score	Number of Crashes	Percentage of Crashes
Carriers with At Least 1 BASIC Score	90,623	100%	133,412	100%
Carriers with No Scores Above Threshold	41,545	45.8%	75,881	56.9%
Carriers with At Least 1 BASIC Score Above Threshold	49,078	54.2%	57,531	43.1%

Further analysis, however, reveals that the higher percentage of crashes attributed to below threshold carriers is simply an artifact of those 41,545 carriers, on average, operating a greater number of power units than the 49,078 carriers with an above threshold score. The former subset of carriers employ nearly twice as many trucks in their fleets ( $N = 1,824,810$  versus  $N = 944,261$ ). Once this is accounted for, crash rates (per 100 power units over a 24-month period) can be observed to be nearly 50 percent higher for carriers with at least one above threshold score ( $M = 6.09$ ) compared to carriers with percentile scores below threshold ( $M = 4.16$ ).

## Relationships Between Percentile Scores and Crash Rates

To further examine which specific BASICs, if any, are functioning as intended (i.e. with higher scores implying greater crash risk), several statistical models were developed. First, ATRI used a log-linear negative binomial regression model to measure the association between BASIC percentile scores and observed crash involvement over a 24-month interval. Each BASIC was analyzed individually to allow for the largest sample size.

### *Unsafe Driving*

Beginning with the Unsafe Driving BASIC, 31,168 motor carriers (6.6% of active carriers) were identified in the database as having sufficient data to calculate a percentile score and crash rate. Using these data, a negative binomial regression analysis was run to examine whether Unsafe Driving BASIC scores have a significant relationship to crash involvement and, if so, whether that relationship is positive or negative.

Table 4 reveals the nature of the relationship between these two variables. It can be interpreted by viewing the row labeled “Unsafe Driving Score,” which is comprised of the percentile ranks given to the 31,168 carriers in the analysis. The parameter estimate associated with this variable ( $B = 0.011$ ) describes the direction of the relationship; positive values imply the variable is positively related to crash rates, while negative values suggest an inverse relationship. Since the estimate is statistically significantly positive in this case ( $\chi^2 = 3,112.43, p \leq .001$ ),<sup>35</sup> it can be concluded that, as Unsafe Driving BASIC scores increase, so do crash rates.

**Table 4. Negative Binomial Regression Model for Unsafe Driving**

Parameter	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	1.797	0.0118	23,166.32	≤ .001	6.032
<i>Unsafe Driving Score</i>	<i>0.011</i>	<i>0.0002</i>	<i>3,112.43</i>	<i>≤ .001</i>	<i>1.011</i>
Scale	1.00*				

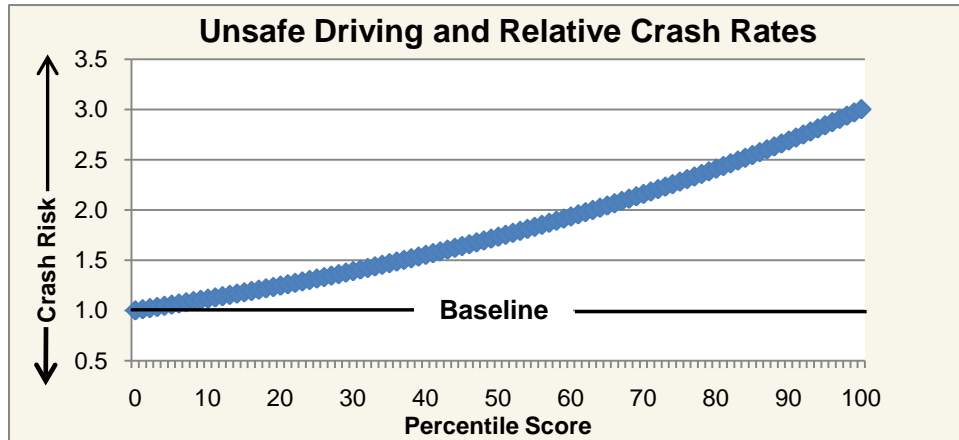
\*Parameter is fixed

Specifically, as scores increase in this BASIC, the relative risk of a crash can be calculated using the negative binomial regression equation.<sup>36</sup> For example, a carrier who has an Unsafe Driving score of 50 is expected, on average, to be approximately 1.73<sup>37</sup> times more likely to be involved in a crash than a carrier with a score of 0; as seen in Figure 8, relative crash rates continue to rise (non-linearly) as scores continue to increase even higher.

<sup>35</sup> P-values less than .05 are considered statistically significant

<sup>36</sup>  $\lambda_i = EXP(\beta X_i + \varepsilon_i)$

<sup>37</sup>  $Exp(B*(percentile\ score)) = Exp(.011*(50)) = 1.73$



**Figure 8. Relationship Between Unsafe Driving Scores and Crash Rates**

*Vehicle Maintenance*

Next, ATRI used data from the 72,885 motor carriers with a Vehicle Maintenance percentile score (15.5% of active carriers) to create another negative binomial regression model. As seen in Table 5, percentile scores in this BASIC demonstrated an almost equally strong positive association with crash rates as did scores in the Unsafe Driving BASIC, considering the size of the *B* coefficient and the corresponding chi square and p-value ( $B = 0.008$ ,  $\chi^2 = 3,239.88$ ,  $p \leq .001$ ).

**Table 5. Negative Binomial Regression Model for Vehicle Maintenance**

Parameter	Parameter Estimate ( <i>B</i> )	Std. Error	Chi-Square	p-value	Exp( <i>B</i> )
Intercept	1.779	0.0095	35,166.07	$\leq .001$	5.925
<i>Vehicle Maintenance Score</i>	0.008	0.0001	3,239.88	$\leq .001$	1.008
Scale	1.00*				

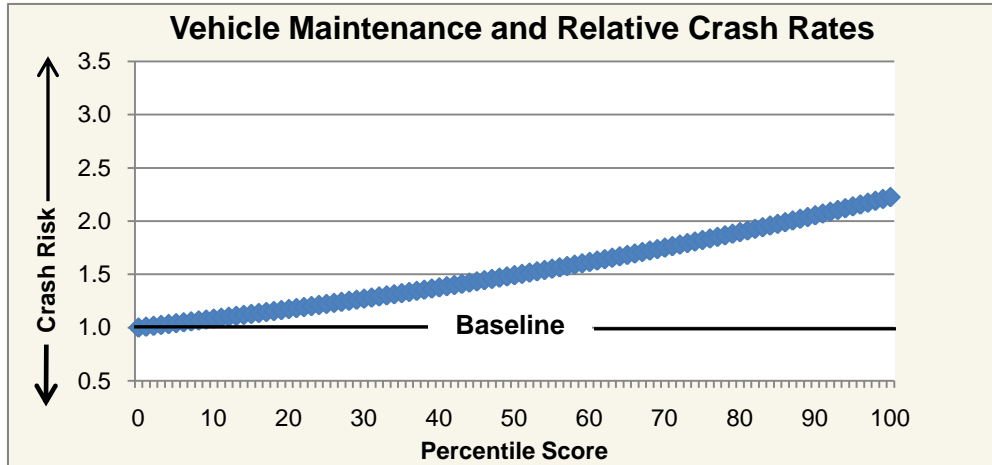
\*Parameter is fixed

As scores increase in this BASIC, the relative risk of a crash rises by a factor of the *B* coefficient.<sup>38</sup> For example, a carrier with a Vehicle Maintenance score of 50 is expected, on average, to be approximately 1.49<sup>39</sup> times more likely to be involved in a crash than a carrier with a score of 0; if the assigned score is 99, the carrier is 2.23<sup>40</sup> times more likely to be involved in a crash compared to a carrier with a score of 0. Figure 9 reveals that this relationship, despite being statistically significant, is not as strong as that found between Unsafe Driving percentile scores and crash rates (compare Figure 8 and Figure 9).

<sup>38</sup>  $\text{Exp}(0.008 * (\text{percentile score}))$

<sup>39</sup>  $\text{Exp}(B * (\text{percentile score})) = \text{Exp}(.008 * (50)) = 1.49$

<sup>40</sup>  $\text{Exp}(B * (\text{percentile score})) = \text{Exp}(.008 * (99)) = 2.23$



**Figure 9. Relationship Between Vehicle Maintenance Scores and Crash Rates**

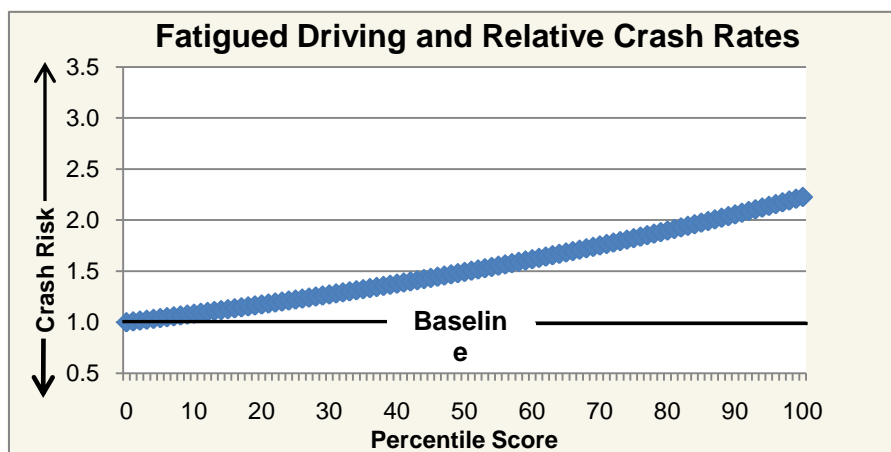
*Fatigued Driving*

Third, 48,884 motor carriers in the database (10.4% of active carriers) were included in the negative binomial regression analysis for the Fatigued Driving BASIC. As seen in Table 6, this BASIC also demonstrated a statistically significant positive association with crash rates ( $B = 0.008$ ,  $\chi^2 = 1,754.87$ ,  $p \leq .001$ ). Again, as scores increase in this BASIC, the relative risk of a crash is expected to rise (non-linearly) by a factor of 0.008, similar to Vehicle Maintenance (see Figure 10).

**Table 6. Negative Binomial Regression Model for Fatigued Driving**

Parameter	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	1.876	0.0136	18,938.24	$\leq .001$	6.524
<i>Fatigued Driving Score</i>	0.008	0.0002	1,754.87	$\leq .001$	1.008
Scale	1.00*				

\*Parameter is fixed



**Figure 10. Relationship Between Fatigued Driving Scores and Crash Rates**

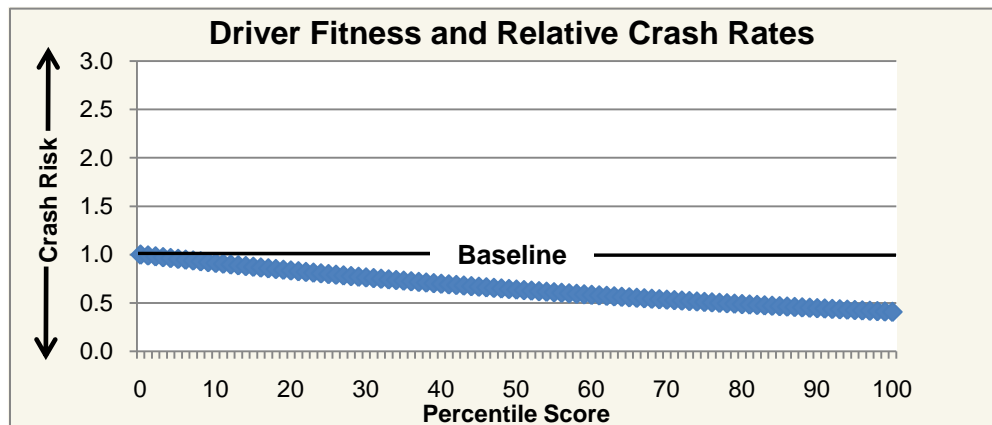
### Driver Fitness

Finally, ATRI examined the two BASICs that are least likely to be scored, Driver Fitness ( $N = 8,680$ ; 1.8% of active carriers) and Controlled Substances and Alcohol ( $N = 2,247$ ; 0.5% of active carriers). Unlike the findings for the previously discussed BASICs, these two BASICs appear to demonstrate negative relationships to crash involvement, meaning higher (i.e. worse) BASIC scores are associated with *lower* crash risk. Table 7 shows the results for the Driver Fitness BASIC, where the parameter estimate is accompanied by a negative sign ( $B = -0.009$ ,  $\chi^2 = 236.95$ ,  $p \leq .001$ ). Therefore, for a percentage point increase in this BASIC, crash rates can be expected to decrease by a factor of 0.991 (see Figure 11).

**Table 7. Negative Binomial Regression Model for Driver Fitness**

Parameter	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	2.970	0.0488	3,705.03	$\leq .001$	19.501
Driver Fitness Score	-0.009	0.0006	236.95	$\leq .001$	0.991
Scale	1.00*				

\*Parameter is fixed



**Figure 11. Relationship Between Driver Fitness Scores and Crash Rates**

### Controlled Substances and Alcohol

Similarly, Table 8 reveals the significantly negative association between the percentile score assigned to the Controlled Substances and Alcohol BASIC and crash involvement ( $B = -0.010$ ,  $\chi^2 = 145.80$ ,  $p \leq .001$ ). For a percentage point increase in this BASIC, crash rates can be expected to decrease by a factor of  $\exp(-0.010) = 0.990$ .

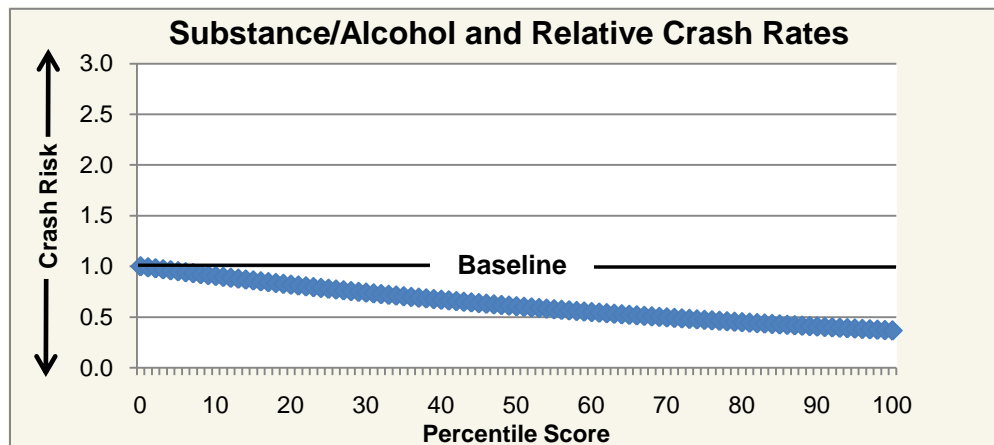
Use of the negative binomial regression equation allows for additional examples. For instance, a carrier with a Controlled Substances and Alcohol score of 50 is expected, on average, to have a lower crash rate than a carrier with a score of 0 by a factor of 0.61; if the score increases to 99, the carrier is further expected to have a lower crash rate by a factor of  $\exp(-.01*(99)) = 0.37$  compared to a carrier with a score of 0 (see Figure 12).



**Table 8. Negative Binomial Regression Model for Controlled Substances and Alcohol**

Parameter	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	2.869	0.0498	3,320.48	≤ .001	17.624
<i>Substance/Alcohol Score</i>	-0.010	0.0008	145.80	≤ .001	0.990
Scale	1.00*				

\*Parameter is fixed



**Figure 12. Relationship Between Controlled Substances and Alcohol Scores and Crash Rates**

### Section Summary

Based on the findings in this section, there is ample evidence to support the SMS methodology for assigning percentile scores to the Unsafe Driving, Fatigued Driving and Vehicle Maintenance BASICs. Percentile scores in these three BASICs accurately reflect relative crash risk, on average. In contrast, there is no statistical support for making intended safety inferences based upon the Driver Fitness or Controlled Substances and Alcohol percentile rankings. In fact, carriers with higher scores in these two BASICs seem to present lower crash risks.

To add perspective, the BASICs that function appropriately capture 99.1 percent of all carriers with at least one assigned BASIC score (i.e. 89,829 carriers have a score in either the Unsafe Driving, Fatigued Driving or Vehicle Maintenance BASIC). On the other hand, the two dysfunctional BASICs apply to just 11.6 percent of carriers who have at least one BASIC score (i.e. 10,500 carriers have a score in either the Driver Fitness or Controlled Substances and Alcohol BASIC).

As a fraction of *all* recently active carriers, roughly one in five carriers has been assigned a score in one of the three BASICs that works as intended, compared to one in fifty possessing one or both of the dysfunctional BASIC scores. Therefore, while the number of carriers adversely affected by flaws in CSA’s percentile scoring mechanism is substantially smaller than the number of carriers receiving valid scores, it is not negligible and must be addressed.

### **Comparing Above vs. Below Threshold Carriers**

Next, ATRI developed a series of negative binomial regression models to compare levels of crash risk for carriers above and below threshold in each of the five public BASICS. For these analyses, “Above Threshold” includes carriers who have percentile scores higher than FMCSA’s designated cutoff(s) and/or Severe Violation(s) that constitute an “Alert” status.<sup>41</sup> A categorical variable was created for each BASIC as follows:

- 1 = Sufficient Roadside Inspection Data But No Score
- 2 = “Alert” (due to Percentile Score and/or a Severe Violation)
- 3 = Score Below Threshold (***reference group***)

For ease of comparison, Group 3 (Score Below Threshold) was made the reference group in the analyses, meaning that all findings will be interpreted as having higher or lower crash rates than carriers with percentile scores below threshold.<sup>42</sup> Again, positive parameter estimates signify increased risk while negative estimates signify decreased risk (relative to the reference group), with p-values less than .05 indicating statistical significance.

Also added to each model was a description of each carrier’s operation type:

- 1 = Passenger Carrier
- 2 = Hazardous Material Carrier
- 3 = General Carrier (***reference group***)

A carrier’s classification affects which percentile cutoff is used, with passenger carriers having the most strict (i.e. lowest) thresholds. Since most carriers (93.2%) fall into Group 3 (General Carriers), that group was chosen as the reference group for all analyses.

Carriers with insufficient roadside inspection data are excluded from all analyses due to the fact that these carriers possess artificially low crash rates and were therefore not considered a viable reference group. Nonetheless, interested readers may look to Appendix A for a breakdown of how many carriers fall into this category within each BASIC ( $N = 470,849$ ).

---

<sup>41</sup> Consequently, the terms “Above Threshold” and “Alert” will be used interchangeably hereafter.

<sup>42</sup> When variables are categorical (e.g. comparing crash rates between groups), one level of each variable is chosen as a reference group (e.g. carriers with below threshold scores). Subsequently, the reference group is not displayed in the table of results; instead, all other levels are fit in the model to show differences in crash rates between each group and the “silent” reference group.

### Unsafe Driving

Beginning with the Unsafe Driving BASIC, 31,170 carriers had sufficient data to be included in the model, and Table 9 breaks down the sample size for each variable considered in the analysis. Notably, the Unsafe Driving BASIC does not allow for carriers to have “Sufficient Roadside Inspection Data But No Score” since violations in this BASIC *trigger* roadside inspections and not vice versa. As a result, this model simply compares crash rates between above and below threshold carriers.<sup>43</sup>

**Table 9. Description of Variables Entered into ATRI’s Unsafe Driving Model**

Variable	Level	N	Percent
Operation Type	1 - (Passenger Carrier)	361	1.2%
	2 - (HazMat Carrier)	5,194	16.7%
	3 - (General Carrier)	25,615	82.2%
Unsafe Driving	1 - (Data, No Score)	N/A	N/A
	2 - (Score Above Threshold)	11,279	36.2%
	3 - (Score Below Threshold)	19,891	63.8%

Table 10 displays the results from the negative binomial regression analysis. Since the model analyzes multiple variables simultaneously, each parameter can be interpreted as holding all other measures constant (rather than treating each variable as existing in its own independent universe). That is, controlling for operation type, a carrier above threshold in the Unsafe Driving BASIC has a crash rate approximately  $\exp(0.554) = 1.74$  times the rate of a carrier with a below threshold Unsafe Driving score, on average ( $B = 0.554, \chi^2 = 2,012.85, p \leq .001$ ). This relationship can be seen in Figure 13.

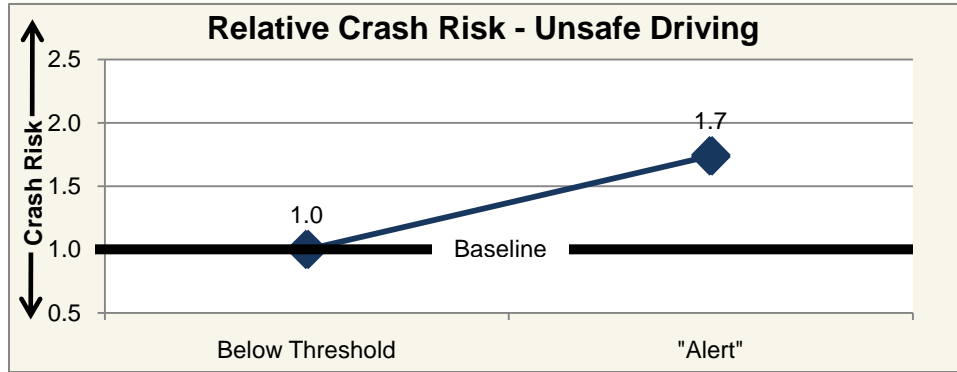
**Table 10. Negative Binomial Regression Model for Differences in Crash Rates – Unsafe Driving**

Parameter	Level	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	-	2.211	.0082	73,219.41	$\leq .001$	9.124
Operation Type	1	-.876	.0587	222.50	$\leq .001$	.417
	2	-.213	.0162	173.13	$\leq .001$	.808
Unsafe Driving	1 <sup>44</sup>	-	-	-	-	-
	2	.554	.0124	2,012.85	$\leq .001$	1.741
Scale	-	1.00*				

\*Parameter is fixed

<sup>43</sup> The model also compares safety levels between operation types – revealing that crash rates are lowest for passenger carriers, followed by hazardous material carriers and finally general carriers – although this comparison is not of particular importance in this research paper.

<sup>44</sup> This category does not exist for the Unsafe Driving BASIC, since violations in that BASIC trigger roadside inspections and not vice versa.



**Figure 13. Safety Differences Between Unsafe Driving Categories**

### Vehicle Maintenance

Next, 110,497 motor carriers had sufficient inspection data to be included in ATRI’s Vehicle Maintenance negative binomial regression model. Again, the primary purpose of this analysis was to investigate differences in crash rates between carriers classified as “Above Threshold” and “Below Threshold.” Additionally, this analysis, as well as the remainder of analyses in this section, allows for safety comparisons with carriers that have “Sufficient Roadside Inspection Data But No Score.” Sample sizes for all three categories are listed in Table 11.

**Table 11. Description of Variables Entered into ATRI’s Vehicle Maintenance Model**

Variable	Level	N	Percent
Operation Type	1 - (Passenger Carrier)	2,306	2.1%
	2 - (HazMat Carrier)	12,959	11.7%
	3 - (General Carrier)	95,232	86.2%
Vehicle Maintenance	1 - (Data, No Score)	37,124	33.6%
	2 - (Score Above Threshold)	21,779	19.7%
	3 - (Score Below Threshold)	51,594	46.7%

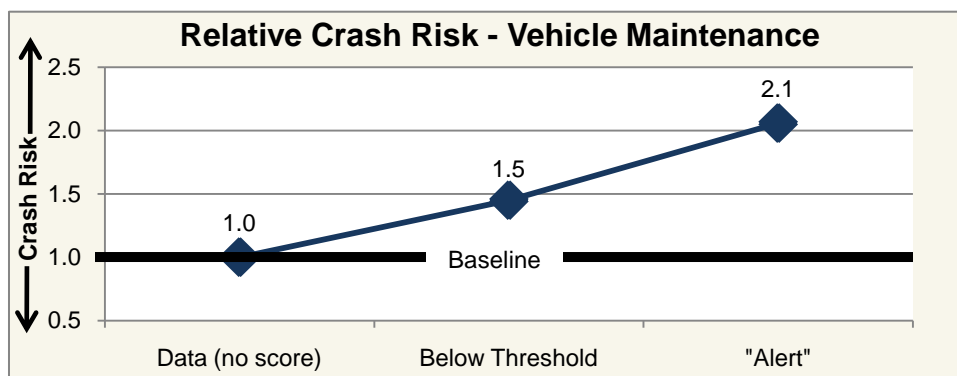
Similar to the findings concerning the Unsafe Driving BASIC, the expected crash rate for a carrier exceeding the Vehicle Maintenance BASIC threshold was found to be 1.42<sup>45</sup> times higher than the rate of a carrier with a percentile score less than FMCSA’s threshold (see Table 12). This time, however, it is apparent that even a score in the acceptable (i.e. below threshold) range is expected to be associated with a higher crash rate than when no score has been issued. That is, a carrier with sufficient vehicle inspection data (but no percentile score) has a significantly lower crash rate than a carrier with a below threshold score by a factor of .69 ( $B = -0.374$ ,  $\chi^2 = 2,621.75$ ,  $p \leq .001$ ). Figure 14 depicts this relationship by allowing the “Sufficient Inspection Data But No Score” carriers to be the reference group.

<sup>45</sup>  $\text{Exp}(0.348) = 1.416$

**Table 12. Negative Binomial Regression Model for Differences in Crash Rates – Vehicle Maintenance**

Parameter	Level	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	-	2.215	.0049	204,695.33	≤ .001	9.159
Operation Type	1	-.572	.0233	602.87	≤ .001	.564
	2	-.299	.0101	880.11	≤ .001	.741
Vehicle Maintenance	1	-.374	.0073	2,621.75	≤ .001	.688
	2	.348	.0085	1,692.15	≤ .001	1.416
Scale	-	1.00*				

\*Parameter is fixed



**Figure 14. Safety Differences Between Vehicle Maintenance Categories**

### Fatigued Driving

The BASIC with the next strongest relationship to crashes was Fatigued Driving. Here, ATRI’s model incorporated 199,137 motor carriers with sufficient data (see Table 13).

**Table 13. Description of Variables Entered into ATRI’s Fatigued Driving Model**

Variable	Level	N	Percent
Operation Type	1 - (Passenger Carrier)	2,784	1.4%
	2 - (HazMat Carrier)	16,446	8.3%
	3 - (General Carrier)	179,907	90.3%
Fatigued Driving	1 - (Data, No Score)	149,455	75.1%
	2 - (Score Above Threshold)	27,721	13.9%
	3 - (Score Below Threshold)	21,961	11.0%

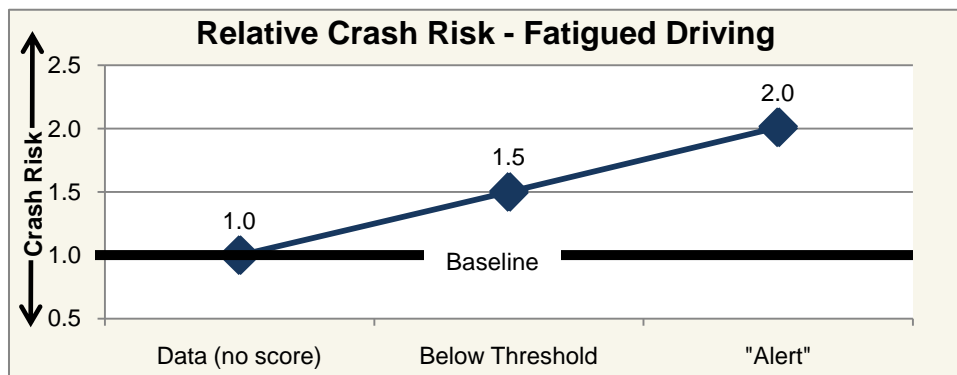
ATRI again found above threshold carriers to have the highest crash rates. Specifically, carriers with an “Alert,” on average, had approximately 1.34 times higher crash rates than below threshold carriers (see Table 14). Also consistent with previous findings, having a score above or below threshold was indicative of greater crash risk than

having sufficient inspection data with no assigned percentile score. Compared to below threshold carriers, those with inspection data but no score had significantly lower crash rates by a factor of .67 ( $B = -0.407$ ,  $\chi^2 = 2,831.92$ ,  $p \leq .001$ ). Figure 15 depicts these findings by allowing the “Sufficient Data, No Score” carriers to be the reference group.

**Table 14. Negative Binomial Regression Model for Differences in Crash Rates – Fatigued Driving**

Parameter	Level	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	-	2.281	.0072	99,814.26	≤ .001	9.789
Operation Type	1	-.526	.0213	612.85	≤ .001	.591
	2	-.255	.0088	833.63	≤ .001	.775
<i>Fatigued Driving</i>	1	-.407	.0077	2,831.92	≤ .001	.665
	2	.293	.0095	954.16	≤ .001	1.340
Scale	-	1.00*				

\*Parameter is fixed



**Figure 15. Safety Differences Between Fatigued Driving Categories**

### *Controlled Substances and Alcohol*

In the Controlled Substances and Alcohol BASIC, there were 199,382 motor carriers with sufficient data to be used in ATRI’s negative binomial model (see Table 15).

**Table 15. Description of Variables Entered into ATRI’s Substance/Alcohol Model**

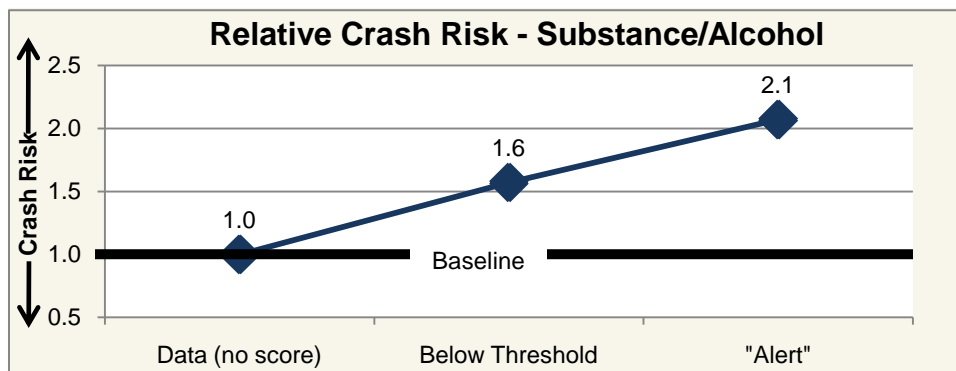
Variable	Level	N	Percent
Operation Type	1 - (Passenger Carrier)	2,816	1.4%
	2 - (HazMat Carrier)	16,460	8.3%
	3 - (General Carrier)	180,106	90.3%
Substance/Alcohol	1 - (Data, No Score)	194,105	97.4%
	2 - (Score Above Threshold)	3,492	1.8%
	3 - (Score Below Threshold)	1,785	0.9%

On average, above threshold carriers were found to have approximately 1.32 times higher crash rates than carriers with below threshold scores. Additionally, carriers with any score (above or below threshold) in the Substance/ Alcohol BASIC were found to have significantly higher crash rates than carriers not assigned a score (see Table 16). Figure 16 depicts this relationship by allowing the “Sufficient Data, No Score” carriers to be the reference group.

**Table 16. Negative Binomial Regression Model for Differences in Crash Rates – Substance/Alcohol**

Parameter	Level	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	-	2.480	.0247	10,058.34	≤ .001	11.944
Operation Type	1	-.582	.0211	764.44	≤ .001	.559
	2	-.233	.0088	706.70	≤ .001	.792
Substance/Alcohol	1	-.452	.0248	331.38	≤ .001	.637
	2	.276	.0303	83.33	≤ .001	1.318
Scale	-	1.00*				

\*Parameter is fixed



**Figure 16. Safety Differences Between Controlled Substance/Alcohol Categories**

Based on the previous set of analyses, which showed a *negative* relationship between carrier Substance/Alcohol percentile scores and crash rates, it was expected that below threshold carriers would have a higher crash rate than above threshold carriers. Further analyses, however, uncovered a simple explanation for the contradictory findings (see Appendix B). Essentially, carriers with an “Alert” in this BASIC primarily receive that status as a result of a Severe Violation rather than due to high percentile scores. Subsequently, carriers with Severe Violations elevated the crash rate for the entire “Alert” group compared to what the group’s crash rate would have been had the analysis only considered carriers above threshold due to high percentile scores.

*Driver Fitness*

Finally, the Driver Fitness negative binomial regression analysis was based on data from 143,358 motor carriers (see Table 17).

**Table 17. Description of Variables Entered into ATRI’s Driver Fitness Model**

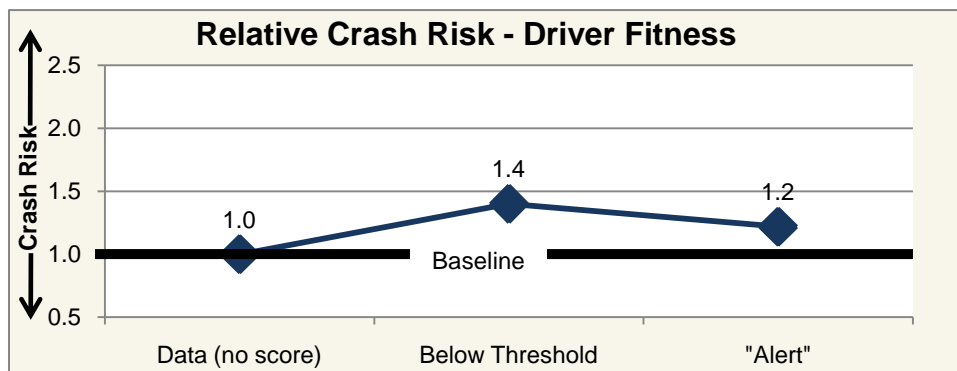
Variable	Level	N	Percent
Operation Type	1 - (Passenger Carrier)	2,170	1.5%
	2 - (HazMat Carrier)	13,933	9.7%
	3 - (General Carrier)	127,255	88.8%
Driver Fitness	1 - (Data, No Score)	132,867	92.7%
	2 - (Score Above Threshold)	7,422	5.2%
	3 - (Score Below Threshold)	3,069	2.1%

In contrast to the other four BASICS, which each found above threshold carriers having significantly higher crash rates than below threshold carriers, the Driver Fitness BASIC revealed unusual findings. In this BASIC, above threshold carriers had a crash rate .87 times *lower* than below threshold carriers. Furthermore, carriers with sufficient roadside inspection information but no score had crash rates .71 times lower than below threshold carriers (see Table 18). Figure 17 depicts this relationship by allowing the “Sufficient Data, No Score” carriers to be the reference group.

**Table 18. Negative Binomial Regression Model for Differences in Crash Rates – Driver Fitness**

Parameter	Level	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	-	2.491	.0192	16,896.00	≤ .001	12.08
Operation Type	1	-.580	.0237	597.50	≤ .001	.560
	2	-.313	.0097	1,050.86	≤ .001	.731
<i>Driver Fitness</i>	1	-.338	.0193	308.56	≤ .001	.713
	2	-.140	.0226	38.48	≤ .001	.869
Scale	-	1.00*				

\*Parameter is fixed



**Figure 17. Safety Differences Between Driver Fitness Categories**



*Section Summary*

In conclusion, in four of the five public BASICs, carriers with an “Alert” had crash rates exceeding those of carriers in all other groups. The one exception was Driver Fitness, where below threshold carriers posed greater safety risks. A graphical depiction of these findings can be seen in Figures 13 through 17. As noted, these figures present the same statistical models as in the respective tables for each BASIC, with the single change of making the “Sufficient Inspection Data But No Score” carriers the reference group.<sup>46</sup> Changing the reference group does not alter any relationships; it simply presents the same set of statistics in a different way.

The figures each compare crash rates *within* each BASIC, meaning the findings are relative. For instance, Figure 15 compares the 21,961 carriers with an “Alert” in the Fatigued Driving BASIC to the 149,455 carriers with “Sufficient Inspection Data But No Score” in the Fatigued Driving BASIC. Alternatively, Figure 17 compares the 3,069 carriers with an “Alert” in the Driver Fitness BASIC to the 132,867 carriers with “Sufficient Inspection Data But No Score” in the Driver Fitness BASIC, and so forth.

While this is informative, it does not reveal which BASICs are most strongly related to safety in absolute terms. To do that, ATRI compared carriers with “Alerts” in each BASIC to a common reference group, carriers with “Sufficient Data But No Alerts.” As revealed in Table 19, the BASICs with the strongest relationship to crashes were the Unsafe Driving and Controlled Substances and Alcohol BASICs; carriers with “Alerts” in these BASICs had 2.45 and 2.41 times higher crash rates than carriers with “No Alerts,” respectively. The next strongest associations were found for the Fatigued Driving and Vehicle Maintenance BASICs; carriers with “Alerts” in these BASICs had 2.02 and 1.99 times higher crash rates than carriers with “No Alerts,” respectively. Lastly, Driver Fitness had the weakest relationship to crashes; yet carriers with an “Alert” in this BASIC still had 1.60 times higher crash rates than carriers with no “Alerts” despite sufficient inspection data.

**Table 19. Absolute Crash Risk Compared to Carriers With Data But No “Alerts”**

“Alert” in:	Crash Risk
Unsafe Driving	2.45
Substance/Alcohol	2.41
Fatigued Driving	2.02
Vehicle Maintenance	1.99
Driver Fitness	1.60

<sup>46</sup> Except for Unsafe Driving, which does not have a “Sufficient Data, No Score” group

### **Available Data and Safety**

Generally speaking, it appears from ATRI's analyses that simply possessing a BASIC score (above or below threshold) implies a carrier has a higher risk of being in a crash than a carrier with no percentile score, regardless of the BASIC. ATRI's analysis seems to suggest that carriers with "sufficient inspection data but no BASIC scores" generally present the lowest safety risk in terms of crash involvement. Comparatively, carriers with below threshold scores have the next lowest crash rates, followed by carriers with "Alerts."

At the highest level, this research creates a clear challenge to industry and government in that it documents how a carrier's observed safety risk can be influenced by the amount of available data for the carrier. For instance, it would be specious to conclude that carriers with insufficient roadside inspection data truly have the safest operations of all motor carriers simply because they are absent from both the SMS and MCMIS crash databases. It is more likely that these "insufficient data" carriers have limited operations and/or exposure and therefore no inspections or crashes; once inspections are performed, the carrier may be found to have one or several "Alerts."

A first step toward correcting this situation is to increase the availability of information for all motor carriers. Currently, FMCSA and its State Partners conduct roughly three million CMV inspections per year (one-third of which discover no driver- or vehicle-based violations). However, a *Proof-of-Concept Test* for Wireless Roadside Inspections (WRIs) found that the wireless technology is capable of increasing the number of annual CMV inspections to approximately 80 million.<sup>47</sup> This would be a significant gain toward increasing the validity of CSA-driven safety inferences.

In particular, expanding the universe of carriers with sufficient inspection data would make it easier to more reliably compare safety differences between fleets. That is, the roughly 270,000 "insufficient data" carriers would transition into another group based on their ratio of "good" to "bad" inspections (i.e. violation-free or not). Meanwhile, carriers that already possess sufficient data will benefit from having a greater number of opportunities to refine their standing within CSA. Receiving exclusively "good" inspections means a carrier will remain among other carriers with very low crash rates (i.e. sufficient data but no score). Conversely, if negative information is present and/or the carrier has one or more BASIC scores, the additional inspections will allow the carrier to amass enough positive data to keep (or shift) those scores below the "Alert" threshold.

---

<sup>47</sup> Capps, G., Franzese, O., Knee, B., Plate, R. & Lascurain, M. B. (2009). *Wireless Roadside Inspection Proof-of-Concept Test*. Washington, DC: Federal Motor Carrier Safety Administration. Available Online: [http://www.fmcsa.dot.gov/facts-research/research-technology/report/FMCSA-RRA-09-007\\_WRI-POC.pdf](http://www.fmcsa.dot.gov/facts-research/research-technology/report/FMCSA-RRA-09-007_WRI-POC.pdf)

## **4.0 SUPPLEMENTARY ANALYSES**

### **Quantity of SMS Data and Safety**

Considering only the motor carriers with at least one BASIC score, a statistical model was created to examine whether how *much* SMS data a scored carrier has presents implications for safety. This model controls for carrier operation type and also for whether a carrier has any “Alerts.” The categories entered into the model are shown below and descriptive statistics for each variable are found in Table 20. The total sample size in this model was 90,603 carriers.

Operation Type:

- 1 = Passenger Carrier (**reference group**)
- 2 = Hazardous Material Carrier
- 3 = General Carrier

Presence of an “Alert”:

- 0 = No “Alerts” (**reference group**)
- 1 = At Least One “Alert”

Number of Assigned BASIC Scores:

- 1 = One BASIC Score (**reference group**)
- 2 = Two BASIC Scores
- 3 = Three BASIC Scores
- 4 = Four BASIC Scores
- 5 = Five BASIC Scores

**Table 20. Description of Variables Entered into ATRI’s Model for Number of BASIC Scores**

<b>Variable</b>	<b>Level</b>	<b>N</b>	<b>Percent</b>
Operation Type	1 - (Passenger Carrier)	1,433	1.6%
	2 - (HazMat Carrier)	9,757	10.8%
	3 - (General Carrier)	79,413	87.6%
Presence of an “Alert”	0 - (No “Alerts”)	41,533	45.8%
	1 - (At Least One “Alert”)	49,070	54.2%
Number of Assigned BASIC Scores	1 - (One BASIC Score)	43,058	47.5%
	2 - (Two BASIC Scores)	26,598	29.4%
	3 - (Three BASIC Scores)	16,526	18.2%
	4 - (Four BASIC Scores)	3,893	4.3%
	5 - (Five BASIC Scores)	528	0.6%

As a result of controlling for whether a carrier has any “Alerts,” this model examines whether crash rates are higher for carriers with multiple BASIC scores, even when all of those scores are below threshold. It also reveals the extent to which carriers with an “Alert” have higher crash rates, holding the total number of assigned scores constant.

As seen in Table 21, compared to a carrier with at least one BASIC score and no “Alerts,” a carrier with one or more “Alerts” would be expected to have a crash rate 1.35 times higher. This again supports FMCSA’s contention that “Alerts” generally do capture the carriers with the highest crash rates, while below threshold carriers are typically safer.

**Table 21. Negative Binomial Regression Model for Number of BASIC Scores**

Parameter	Level	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	-	1.477	.0290	2,586.55	≤ .001	4.381
Operation Type	2	.191	.0310	38.08	≤ .001	1.211
Operation Type	3	.497	.0293	287.93	≤ .001	1.643
Presence of an “Alert”	1	.299	.0074	1,631.09	≤ .001	1.348
Number of Scores	2	.154	.0084	336.75	≤ .001	1.166
Number of Scores	3	.333	.0099	1,142.35	≤ .001	1.396
Number of Scores	4	.514	.0178	829.88	≤ .001	1.671
Number of Scores	5	.602	.0455	175.23	≤ .001	1.825
Scale	-	1.00*				

\*Parameter is fixed

Despite lower crash rates among below threshold carriers, however, there is still a clear trend that crash rates increase as the number of assigned BASIC scores increases. In other words, a carrier with two BASIC scores has a 1.17 times higher crash rate than a carrier with only one BASIC score, even when those scores are in the acceptable (below threshold) range. Moreover, the crash rate differential rises to 1.40 when a carrier has scores assigned in three BASICs; to 1.67 when a carrier has scores in four BASICs; and to 1.83 when a carrier has scores assigned in all five public BASICs.

These findings present an interesting issue. From this analysis alone, it would appear that the quantity of SMS data a carrier has may be a better predictor of crashes than whether those data include above threshold scores. After all, possessing five BASIC scores is associated with a 1.83 times higher crash rate, which exceeds the 1.35 times higher crash rate associated with having an “Alert.” To address this possibility, ATRI’s next statistical model examines the relationship between crash rates and the quantity of specifically negative SMS data (i.e. “Alerts”).

**Quantity of Negative SMS Data and Safety**

Since a positive association was found between the number of assigned BASIC scores and safety, ATRI examined whether the number of *Above Threshold* BASIC scores was an even better predictor of crash rates. The results of this analysis are critically important. If the sheer number of (above or below threshold) BASIC scores says as much about safety as the number of “Alerts,” then the rationale behind SMS thresholds would be seriously challenged. Conversely, if the number of “Alerts” is more strongly related to crashes, then there would be additional support for FMCSA’s methodology.

The number of “Alerts” assigned to a carrier was entered into the model, with operation type included as a control variable. All categories in the model are described below, with descriptive statistics for each variable found in Table 22. The total sample size in this model was 91,848 carriers.

Operation Type:

- 1 = Passenger Carrier (**reference group**)
- 2 = Hazardous Material Carrier
- 3 = General Carrier

Number of “Alerts”:

- 0 = At Least One BASIC Score but Zero “Alerts” (**reference group**)
- 1 = One “Alert”
- 2 = Two “Alerts”
- 3 = Three “Alerts”
- 4 = Four “Alerts”
- 5 = Five “Alerts”

**Table 22. Description of Variables Entered into ATRI’s Model for Number of “Alerts”**

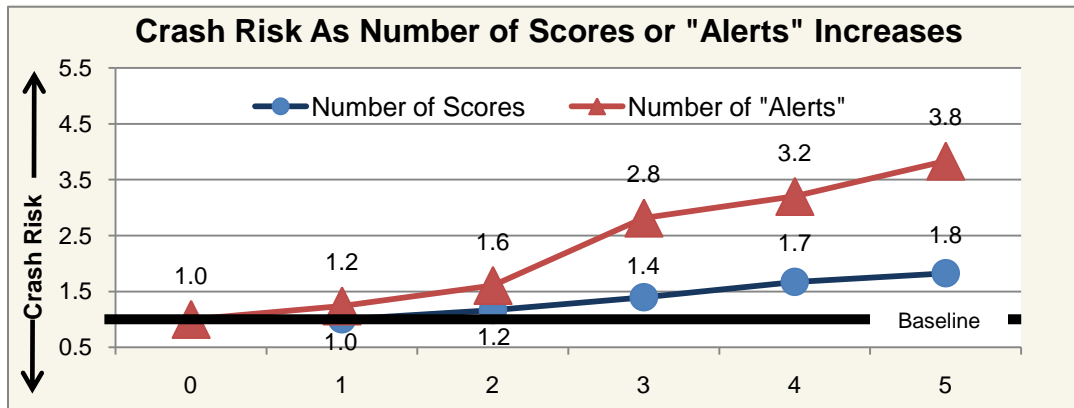
Variable	Level	N	Percent
Operation Type	1 - (Passenger Carrier)	1,643	1.8%
	2 - (HazMat Carrier)	9,904	10.8%
	3 - (General Carrier)	80,301	87.4%
Number of “Alerts”	0 - (Scores But No “Alerts”)	41,533	45.2%
	1 - (One “Alert”)	34,346	37.4%
	2 - (Two “Alerts”)	11,812	12.9%
	3 - (Three “Alerts”)	3,058	3.3%
	4 - (Four “Alerts”)	946	1.0%
	5 - (Five “Alerts”)	153	0.2%

Reviewing Table 23, it is clear that the number of “Alerts” a carrier has is indeed the better predictor of crash involvement. Compared to a carrier with at least one BASIC score and no “Alerts,” a carrier with a single “Alert” is expected to have a crash rate 1.24 times higher; a carrier with two “Alerts” is expected to have a crash rate 1.61 times higher; a carrier with three “Alerts” is expected to have a crash rate 2.81 times higher; a carrier with four “Alerts” is expected to have a crash rate 3.20 times higher; and a carrier with an “Alert” in all five public BASICs has a crash rate nearly four times higher. Figure 18 presents the findings from Table 23 alongside those from Table 21.

**Table 23. Negative Binomial Regression Model for Number of “Alerts”**

Parameter	Level	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	-	1.490	.0272	3,007.95	≤ .001	4.438
Operation Type	2	.332	.0291	130.06	≤ .001	1.394
Operation Type	3	.573	.0274	438.84	≤ .001	1.774
Number of “Alerts”	1	.215	.0078	769.70	≤ .001	1.240
Number of “Alerts”	2	.475	.0109	1,886.40	≤ .001	1.608
Number of “Alerts”	3	1.035	.0192	2,894.15	≤ .001	2.814
Number of “Alerts”	4	1.164	.0336	1,200.61	≤ .001	3.202
Number of “Alerts”	5	1.344	.0824	265.98	≤ .001	3.833
Scale	-	1.00*				

\*Parameter is fixed



**Figure 18. Relative Crash Risk as the Number of Scores or “Alerts” Increases**

The above findings compare carriers with “Alerts” to carriers with scores and no “Alerts.” When the model is run to compare carriers with “Alerts” against the 108,540 carriers with “sufficient inspection data but no percentile scores,” the figures are even more compelling. In fact, piecing together all groups of carriers examined within the SMS, ATRI presents a final statistical model that contains recommendations for how safety information could be portrayed to the public to better describe carrier safety levels.

### **Making Safety Inferences from CSA: Recommendations**

Thus far, ATRI has demonstrated that several individual BASICs function well while issues persist in the Controlled Substance/Alcohol and especially Driver Fitness BASICs. Essentially, each BASIC allows carriers to be classified into four distinct groups:

- Insufficient Roadside Inspection Data
- Sufficient Inspection Data But No Score
- Percentile Score Below Threshold
- “Alert” (due to Percentile Score and/or a Severe Violation)

While carriers with “insufficient data” typically have the lowest crash rates, this is an artifact of there being very few observations among these carriers, 96 percent of whom are not found in the MCMIS crash file. More is known concerning the other three groups of carriers, with “sufficient data but no score” carriers maintaining better safety records, on average, than carriers with one or more BASIC scores assigned. This is not surprising considering that a carrier that only receives violation-free inspections will not receive a BASIC score until an inspection uncovers driver- or vehicle-based violations.

Finally, among carriers with scores, it is true that the number of “Alerts” reveals more about fleet safety than the number of below threshold scores. It is with this understanding that ATRI proposes an alternative scoring mechanism be used to display a carrier’s relative safety status.

The SMS could be redesigned to create multiple safety *classifications* (e.g. A, B, C series) to indicate the level of crash risk presented by carriers, rather than relying on a flawed percentile scoring system. While FMCSA and motor carriers could continue utilizing targeted BASIC information as an internal compliance tool, creating new safety classifications for carriers, as suggested below, would allow for the public to view a profile of carriers that provides more reliable indications of fleet safety.

To that effect, a final negative binomial regression model was run using the following classifications, with the “Sufficient Data, No Score” carriers chosen as the reference group:

- A = Sufficient Inspection Data But No Score in Any BASIC (***reference group***)
- B = At Least One Assigned BASIC Score (but no “Alerts”)
- C-1 = One “Alert”
- C-2 = Two “Alerts”
- C-3 = One “Alerts”
- C-4 = One “Alerts”
- C-5 = One “Alerts”

Once again, carrier operation type is also considered in the analysis as a control variable with passenger carriers listed as the reference group. Table 24 displays the sample size in each group for the 200,388 carriers used in the model.

**Table 24. Description of Variables Entered into ATRI’s Model for Proposed Safety Categories**

Variable	Level	N	Percent
Operation Type	1 - (Passenger Carrier)	3,221	1.6%
	2 - (HazMat Carrier)	16,542	8.3%
	3 - (General Carrier)	180,625	90.1%
Proposed Safety Category	A - (Sufficient Inspection Data But No Scores)	108,540	54.2%
	B - (Scores But No “Alerts”)	41,533	20.7%
	C-1 - (One “Alert”)	34,346	17.1%
	C-2 - (Two “Alerts”)	11,812	5.9%
	C-3 - (Three “Alerts”)	3,058	1.5%
	C-4 - (Four “Alerts”)	946	0.5%
	C-5 - (Five “Alerts”)	153	0.1%

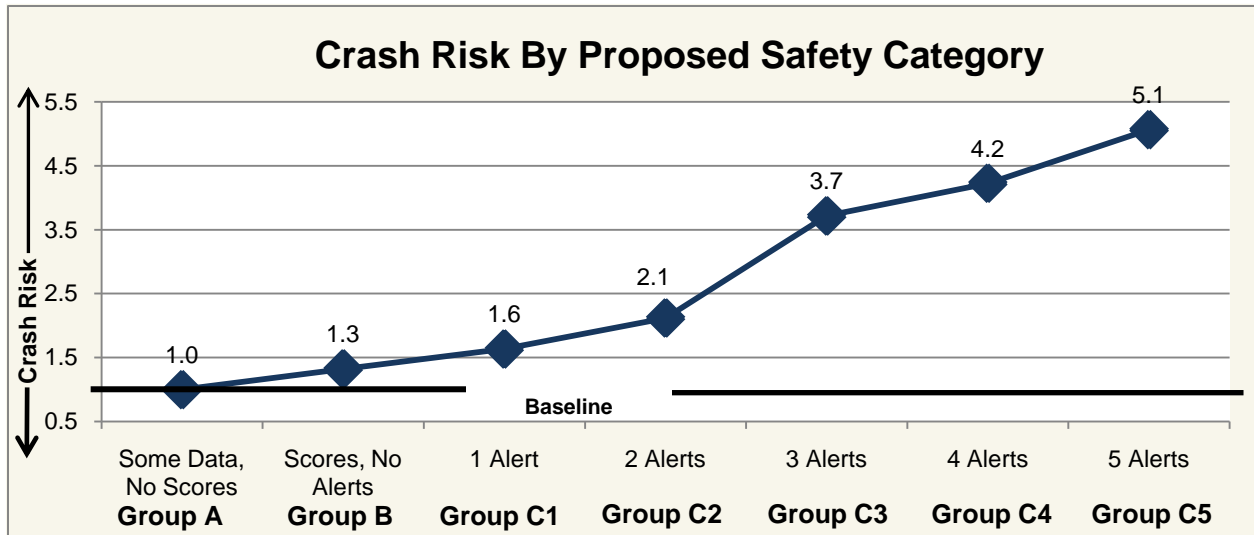
Table 25 and Figure 19 reveal the results from the regression model. As hypothesized, all groups of carriers displayed significantly higher crash rates than Group A (carriers with Sufficient Data But No Score). Comparatively, Group B had 1.32 times higher crash rates and crash rates rose significantly from there for the variants of Group C. At the maximum number of “Alerts” (i.e. five), carriers on average displayed 5.06 times higher crash rates than the carriers in Group A.

**Table 25. Negative Binomial Regression Model for Proposed Safety Categories**

Parameter	Level	Parameter Estimate (B)	Std. Error	Chi-Square	p-value	Exp(B)
Intercept	-	1.203	.0199	3,665.88	≤ .001	3.332
Operation Type	2	.300	.0214	195.65	≤ .001	1.350
Operation Type	3	.587	.0199	873.63	≤ .001	1.799
Safety Category	B	.279	.0062	2,014.39	≤ .001	1.322
Safety Category	C-1	.491	.0066	5,614.24	≤ .001	1.635
Safety Category	C-2	.751	.0101	5,509.64	≤ .001	2.119
Safety Category	C-3	1.313	.0188	4,875.99	≤ .001	3.717
Safety Category	C-4	1.441	.0333	1,868.00	≤ .001	4.225
Safety Category	C-5	1.622	.0823	388.57	≤ .001	5.064
Scale	-	1.00*				

\*Parameter is fixed





**Figure 19. Relative Crash Risk by Proposed Safety Category**

ATRI concludes that assigning motor carriers into the seven categories found in Figure 19 presents far more logical and reliable information about fleet safety than the currently published SMS percentile scores.

Group A is comprised of fleets that have sufficient inspection data, yet not enough negative data to generate a BASIC score. ATRI’s analysis suggests these carriers present the lowest crash risk. Carriers in Group B, who have percentile scores but no “Alerts” also have very low crash rates. Crash risk increases dramatically only after a carrier has been assigned multiple “Alerts,” with risk nearly doubling between having two versus three “Alerts.” This is likely reflective of pervasive safety problems that are reflected both in poor SMS scores and high crash frequencies.

Chief among the key findings from this model is that the carriers with sufficient roadside inspection data, but no BASIC scores, are just as safe, and even present slightly less crash risk than carriers with assigned percentile scores below FMCSA’s thresholds. This is particularly important since many shippers, brokers and other trucking stakeholders currently perceive the SMS to only indicate safety when a carrier possesses a below threshold score. While below threshold carriers do indeed have significantly lower crash rates than carriers with “Alerts,” this analysis confirms that carriers who have sufficient roadside inspection data but have not generated a score should also be construed as safe.<sup>48</sup>

<sup>48</sup> “A lack of a ranking for smaller carriers due to lack of exposure, or inspections, or simply by having only perfect clean inspections means they are overlooked by brokers or shippers for potential freight business – even if a particular carrier is actually a safe operator with a perfect safety record.” Source: Kilcarr, S. Committee hearing illuminates growing tension over CSA. *Fleet Owner*. September 14, 2012. Available Online: <http://fleetowner.com/regulations/committee-hearing-illuminates-growing-tension-over-csa>

Motor carriers should examine their place within Figure 19. This figure describes estimates of crash risk calculated from hundreds of thousands of carriers presently in each of the seven categories. Presumably, then, there is something about the specific categories that influences crash risk. As a fleet adopts new strategies to alter roadside performance, and therefore transitions into a new group, the carrier can reasonably expect to resemble the characteristics of that new group, including experiencing a change in relative crash risk.

## **5.0 CAVEATS**

Negative binomial modeling is typically used to predict future events. However, in this analysis, the SMS and crash data used were both taken from the same historical period, as opposed to using crash data from a two-year period *after* SMS profiles. Therefore, the findings herein should not be interpreted as predicting *future* crashes based on BASIC measures; rather, the findings are descriptive in nature, examining current safety risk differences according to the previous two years of crash and SMS information.

Furthermore, the analyses in this paper consider only crash frequency as a dependent variable and not crash severity, which is also a factor in determining BASIC percentile rankings. As an example, a seatbelt violation may not be a good indicator of crash involvement, yet may still be a reasonably good predictor of crash severity. It is therefore possible that incorporating crash severity (i.e. number of injuries and/or fatalities) into the analyses could alter the findings and conclusions presented in this report.

Finally, as with any statistical analysis, it should be understood that not all individual circumstances can be accurately described by a regression model. In other words, ATRI's findings may not be true for every individual motor carrier; however, they do describe statistically significant trends based on data from hundreds of thousands of motor carriers.

## **6.0 CONCLUSION**

This paper has examined which of CSA's five public BASICs can be used for assessing fleet safety in terms of crash involvement. As it is currently designed, CSA has a number of defects that still need to be addressed. Most notably, the Driver Fitness BASIC demonstrates several poor qualities – percentile scores in this BASIC are *negatively* related to crash rates and carriers with an “Alert” in this BASIC have *lower* crash rates than carriers with below threshold Driver Fitness scores. Although not as comprehensively flawed, ATRI also found problems suggesting that FMCSA's severity weighting methodology is not functioning properly in the Controlled Substances and Alcohol BASIC.

Nonetheless, ATRI found that “Alerts” (which include high percentile scores and Severe Violations) are generally good indicators of safety. This is true in the Unsafe Driving, Fatigued Driving, Vehicle Maintenance and Controlled Substances and Alcohol BASICs.

Like UMTRI, ATRI's analysis also revealed that carriers with any percentile score (above *or* below threshold) tend to have higher crash rates than carriers that have not been issued BASIC scores. This is somewhat intuitive since CSA essentially tracks negative data (i.e. violations); therefore, ATRI used what is known about different carrier classifications to identify new approaches for categorizing safety. Essentially, carriers may have:

- Insufficient roadside inspection data to be evaluated
- Sufficient roadside inspection data but not enough violations to be assigned a BASIC score
- Sufficient roadside inspection violations to be assigned a BASIC score but enough violation-free inspections to keep that score below threshold
- Sufficient roadside inspection violations to outweigh clean inspections and be issued one or more “Alerts.”

FMCSA even acknowledges differences in safety between these types of carriers, granting lower Inspection Selection System (ISS) and e-clearance values to the first two groups while targeting carriers with “Insufficient Roadside Inspection Data” or “Alerts.” It is disconcerting then, that other trucking industry stakeholders (e.g. shippers and brokers) misperceive carriers without scores as unsafe, even if it is due to having exclusively clean inspections.<sup>49</sup>








---

<sup>49</sup> Kilcarr, S. Committee hearing illuminates growing tension over CSA. *Fleet Owner*. September 14, 2012. Available Online: <http://fleetowner.com/regulations/committee-hearing-illuminates-growing-tension-over-csa>

To better clarify precisely which carriers have what extent of crash risk, ATRI developed a final statistical model capable of reliably communicating safety information to the public. While FMCSA and motor carriers may continue using current CSA profiles to identify specific areas where regulatory compliance can be improved, ATRI’s model does a superior job demonstrating a link to actual safety.

In conclusion, ATRI found that percentile scores are defective in two BASICs and even “Alerts” do not consistently identify the riskiest carriers within all five BASICs. On the other hand, a new classification system could be designed that allows trucking stakeholders to better gauge fleet safety by classifying carriers into groups based on where they fall in the following chart (see Table 26).

**Table 26. Empirically Determined Continuum of Safety Risk**

Classification Group	Description	Level of Safety Risk	
		Low	High
Group A	Sufficient data in at least one BASIC, but no scores		
Group B	Scores in at least one BASIC, but no "Alerts"		
Group C-1	1 "Alert"		
Group C-2	2 "Alerts"		
Group C-3	3 "Alerts"		
Group C-4	4 "Alerts"		
Group C-5	5 "Alerts"		

## REFERENCES

- American Transportation Research Institute. *Compliance, Safety, Accountability: Evaluating A New Safety Measurement System And Its Implications*. (Unpublished manuscript)
- Atkins, D. C. & Gallop, R. J. (2007). Rethinking how family researchers model infrequent outcomes: A tutorial on count regression and zero-inflated models. *Journal of Family Psychology*, 21(4), 726-735.
- Capps, G., Franzese, O., Knee, B., Plate, R. & Lascurain, M. B. (2009). *Wireless Roadside Inspection Proof-of-Concept Test*. Washington, DC: Federal Motor Carrier Safety Administration. Available Online: [http://www.fmcsa.dot.gov/facts-research/research-technology/report/FMCSA-RRA-09-007\\_WRI-POC.pdf](http://www.fmcsa.dot.gov/facts-research/research-technology/report/FMCSA-RRA-09-007_WRI-POC.pdf)
- Federal Motor Carrier Safety Administration. *Compliance, Safety, Accountability (CSA)*. Available Online: <http://csa.fmcsa.dot.gov/default.aspx>
- Federal Motor Carrier Safety Administration. (2012). *Review of Wells Fargo Equity Research Report on Compliance, Safety, Accountability*. Available Online: [http://www.cvsa.org/news/documents/2012/FMCSA%20Analysis%20of%20Wells%20Fargo%20Report%20re%20CSA%20-%20FMC-120124-006\).pdf](http://www.cvsa.org/news/documents/2012/FMCSA%20Analysis%20of%20Wells%20Fargo%20Report%20re%20CSA%20-%20FMC-120124-006).pdf)
- Gallo, A. P. & Busche, M. CSA: Another look with similar conclusions. *Wells Fargo Securities Equity Research*. July 12, 2012.
- Gimpel, J. Statistical issues in the safety measurement and inspection of motor carriers. *Alliance for Safe, Efficient and Competitive Truck Transportation*. July 10, 2012. Available Online: <http://asectt.blogspot.com/2012/07/news-brief-university-of-maryland-study.html>
- Green, P. E. & Blower, D. (2011). *Evaluation of the CSA 2010 Operational Model Test*. (Report No. FMCSA-RRA-11-019). Washington, DC: Federal Motor Carrier Safety Administration.
- Iyoob, I. SMS BASIC scores are not valid predictors of crash frequency. *Alliance for Safe, Efficient and Competitive Truck Transportation*. June 25, 2012. Available Online: <http://asectt.blogspot.com/2012/06/sms-basic-scores-are-not-valid.html>
- John A. Volpe National Transportation Systems Center. (2009). *Comprehensive Safety Analysis 2010: Carrier Safety Measurement System Violation Severity Weights*. Washington, DC: Federal Motor Carrier Safety Administration. Available Online: <http://www.regulations.gov/#!documentDetail;D=FMCSA-2004-18898-0161>
- John A. Volpe National Transportation Systems Center. (2012). *Safety Measurement System (SMS) Methodology, Version 2.2*. Washington, DC: Federal Motor Carrier Safety Administration. Available Online: <https://csa.fmcsa.dot.gov/Documents/SMSMethodology.pdf>
- Kilcarr, S. Committee hearing illuminates growing tension over CSA. *Fleet Owner*. September 14, 2012. Available Online: <http://fleetowner.com/regulations/committee-hearing-illuminates-growing-tension-over-csa>
- Long, J. S. (1997). *Regression models for categorical and limited dependent variables*. Thousand Oaks, CA: Sage Publications.

## APPENDIX A

### Full Descriptive Statistics

Variable	Value	N	Percent
Operation Type	Passenger Carrier	10,505	2.2%
	HazMat Carrier	21,482	4.6%
	General Carrier	438,862	93.2%
Unsafe Driving	Insufficient Data	439,679	93.4%
	Data, No Score <sup>50</sup>	N/A	N/A
	Score Above Threshold	11,279	2.4%
	Score Below Threshold	19,891	4.2%
Fatigued Driving	Insufficient Data	271,712	57.7%
	Data, No Score	149,455	31.7%
	Score Above Threshold	27,721	5.9%
	Score Below Threshold	21,961	4.7%
Vehicle Maintenance	Insufficient Data	360,352	76.5%
	Data, No Score	37,124	7.9%
	Score Above Threshold	21,779	4.6%
	Score Below Threshold	51,594	11.0%
Substance/Alcohol	Insufficient Data	271,467	57.7%
	Data, No Score	194,105	41.2%
	Score Above Threshold	3,492	0.7%
	Score Below Threshold	1,785	0.4%
Driver Fitness	Insufficient Data	327,491	69.6%
	Data, No Score	132,867	28.2%
	Score Above Threshold	7,422	1.6%
	Score Below Threshold	3,069	0.7%

<sup>50</sup> This category does not exist for the Unsafe Driving BASIC, since violations in that BASIC trigger roadside inspections and not vice versa

## APPENDIX B

### *Explaining the Controlled Substances and Alcohol BASIC*

ATRI explored why the Controlled Substances and Alcohol BASIC functions well in one sense (i.e. carriers with an “Alert” have higher crash rates than carriers with scores below threshold) yet poorly in another (i.e. percentile scores are negatively related to crash rates).

The first discovery helped to explain why a negative relationship was found between percentile scores and crash involvement. Specifically, ATRI found that only 642 carriers possess high (i.e. above threshold) percentile scores in the Controlled Substances and Alcohol BASIC. Of these 642 carriers, nearly 80 percent ( $N = 512$ ) have a crash rate of zero.<sup>51</sup> With these carriers in the analysis, it is no surprise that a negative relationship would surface. Future research should explore what unique factors exist within the set of 512 carriers that they would be assigned high percentile scores in this BASIC despite presenting no safety risk whatsoever (in terms of observed crashes).

The second discovery was that receiving an “Alert” in the Controlled Substances and Alcohol BASIC is most often the result of having a Severe Violation; not due to high percentile scores. In fact, of the 3,476 carriers with “Alerts,” 2,834 (81.5%) have an “Alert” due exclusively to a Severe Violation. As seen below, this is the only BASIC where carriers are *primarily* given an “Alert” due to Severe Violations.

BASIC	Percent of Carriers with an “Alert” due to a Severe Violation
Unsafe Driving	0.00018%
Vehicle Maintenance	0.022%
Fatigued Driving	0.028%
Driver Fitness	24.2%
<b>Controlled Substances and Alcohol</b>	<b>81.5%</b>

Moreover, Controlled Substances and Alcohol was one of only two BASICs<sup>52</sup> in which crash rates for carriers with Severe Violations exceeded crash rates for carriers with above threshold percentile scores. In the case of the Controlled Substances and Alcohol BASIC, the crash rates for carriers with Severe Violations were more than *twice* as high. Given the large number of carriers with a Severe Violation in that BASIC, it is clear why ATRI found Above Threshold carriers to suddenly have higher crash rates than below threshold carriers once Severe Violators were included in the analysis.

<sup>51</sup> For all other BASICs, this figure was between approximately 50 to 60 percent

<sup>52</sup> The other was Driver Fitness

In conclusion, the Controlled Substances and Alcohol BASIC has the fewest percentile scores issued and the greatest number of Severe Violations. What ATRI discovered is that Severe Violations are better indicators of crash risk in this BASIC than is the methodology for calculating percentile scores. Similar to the Driver Fitness BASIC, it is likely that FMCSA's severity weighting methodology places too much weight on safety-unrelated violations and too little weight on safety-critical violations.

Overall, findings show that, in the Controlled Substances and Alcohol BASIC, carriers "below threshold" (Group 1) have *higher* crash rates than carriers "above threshold due to percentile scores" (Group 2). Meanwhile, carriers "above threshold due to a Severe Violation" have markedly higher crash rates than both Groups 1 and 2. This is why carriers with an "Alert" (which includes carriers with a Severe Violation OR a high percentile score) have higher crash rates than carriers with a score below threshold.





950 N. Glebe Road  
Arlington, VA  
(703) 838-1966  
[atri@trucking.org](mailto:atri@trucking.org)  
[www.atri-online.org](http://www.atri-online.org)