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Statistical Investigation of Road and Railway Hazardous Materials Transportation Safety

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STATISTICAL INVESTIGATION OF ROAD AND RAILWAY HAZARDOUS MATERIALS TRANSPORTATION SAFETY

by

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STATISTICAL INVESTIGATION OF ROAD AND RAILWAY HAZARDOUS MATERIALS TRANSPORTATION SAFETY

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Transportation of hazardous materials (hazmat) in the United States (U.S.) constituted 22.8% of the total tonnage transported in 2012 with an estimated value of more than 2.3 billion dollars. As such, hazmat transportation is a significant economic activity in the U.S. However, hazmat transportation exposes people and environment to the infrequent but potentially severe consequences of incidents resulting in hazmat release. Trucks and trains carried 63.7% of the hazmat in the U.S. in 2012 and are the major foci of this dissertation. The main research objectives were 1) identification and quantification of the effects of different factors on occurrence and consequences of hazmat-related incidents, towards identifying effective policies and countermeasures for improving safety and; 2) quantifying components of risk of hazmat transportation for costs prediction, planning purposes, or short-term decision-making.

A comprehensive review of literature, study framework, and available data led to identification of six foci for this dissertation: 1) estimation of hazmat release statistical models for railroad incidents; 2) estimation of rollover and hazmat release statistical models for Cargo Tank Truck (CTT) crashes; 3) analyzing hazmat-involved crashes at highway-rail grade crossings (HRGCs); 4) model-based and non-model-based methods for classifying hazmat release from trains and CTTs; 5) estimation of macroscopic-level

statistical models for frequency and severity of rail-based crude oil release incidents; and 6) estimation of statistical models for types and consequences of rail-based crude oil release incidents.

Some of the findings of this research include: train derailments increased hazmat release probability more than other incident types; non-collision CTT crashes were more likely to result in rollovers, while rolling over increased the likelihood of hazmat release; at HRGCs, flashing signal lights were associated with lower hazmat release probability from trucks; increase in volume and distance of crude oil shipped from one state to another led to greater frequency and severity of incidents between the two states; and in rail-based crude oil release incidents, non-accident releases were associated with higher probability of gas dispersion, and lower probability of fire and explosion. Based on the results, recommendations regarding policies and countermeasures for improving safety are provided.

To my parents

Firoozeh and Mahbod,

My wife and daughter

Sara and Rosemary,

And my sister and brother-in-law

Niloofar and Reza

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CHAPTER 1 INTRODUCTION

1.1 Background

Transportation of hazardous materials (hazmat) exposes people and environment (e.g., air and water) to the infrequent but potentially severe consequences of incidents resulting in hazmat release. Such incidents, depending on the type of hazmat, quantity of release, environment and spatial/temporal characteristics of the incidents may impose monetary and non-monetary (e.g., pain and suffering of incident victims) costs upon the society. For example, in a 2015 train incident in Maryville, Tennessee release of 29,710 gallons of Acrylonitrile led to fire, explosion, gas dispersion, water pollution, environmental damage, 195 injuries, evacuation of 5,000 people, and $7.7 million worth of damages (Pipeline and Hazardous Materials Safety Administration and Office of Hazardous Materials Safety 2018). Improving safety of hazmat transportation by decreasing the frequency of such incidents and alleviating their consequences from safety planning or shipper/carrier points of view benefits society.

Substances are categorized as hazmat if they can cause injury, death and serious illness, or put a significant threat to the human population or the environment due to their chemical, physical or other characteristics (Lee 2014). The U.S. Department of Transportation defines hazmat as belonging to one of the nine hazard classes, presented in Table 1.1, along with the U.S. shipment amounts and ratios in 2012 according to the U.S. Census Bureau’s 2012 Commodity Flow Survey (the latest publicly available Commodity Flow Survey at this time) (U.S. Department of Transportation and U.S. Department of Commerce 2015).

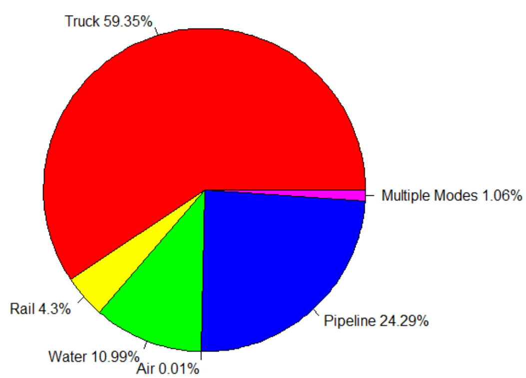
Table 1.1 2012 Hazardous Material Shipment Characteristics by Hazard Class for the U.S.

Class	Description	Value		Ton		Ton-miles	
		2012 (million dollars)	Percent of total	2012 (1000s)	Percent of total	2012 (million s)	Percent of total
1	Explosives	18397	0.79%	4045	0.16%	1012	0.33%
2	Gases	125054	5.36%	164794	6.39%	33157	10.78%
3	Flammable and combustible liquids	2016681	86.39%	2203490	85.42%	204573	66.52%
4	Flammable solids	5415	0.23%	11321	0.44%	5804	1.89%
5	Oxidizers and Organic Peroxides	7562	0.32%	12025	0.47%	5479	1.78%
6	Toxic (Poisonous) Materials and Infectious Substances	15196	0.65%	7612	0.30%	3607	1.17%
7	Radioactive Materials	12288	0.53%	NA	NA	39	0.01%
8	Corrosive Materials	75850	3.25%	125287	4.86%	37784	12.29%
9	Miscellaneous Dangerous Goods	57981	2.48%	51006	1.98%	16068	5.22%
	Total	**2334424**	**100.00%**	**2580153**	**100.00%**	**307523**	**100.00%**

(Source: 2012 Commodity Flow Survey (U.S. Department of Transportation and U.S. Department of Commerce 2015)), NA: Not Available

Hazmat transportation constitutes a considerable portion of freight transportation and is a significant and non-negligible economic activity in the U.S. According to the 2012 Commodity Flow Survey, 2,580,153 thousand tons (307,524 million ton-miles) of hazmat was transported in 2012, with the approximate monetary value of $2,334,425,000. This constitutes 22.8% of the total tonnage and 10.4% of the total ton-miles of freight transportation. Demand for hazmat transportation in the U.S. has grown over the past decade, specifically due to transportation of crude oil. A 15.6% increase in the tonnage and 49.4% increase in the value of the transported hazmat since 2007 is reported in the 2012 Commodity Flow Survey. These statistics justify the need to study the safety aspects of hazmat transportation in the U.S.

Hazmat is transported by different modes. Highway, rail, water, air and pipelines (and also multimodal, e.g. combination of truck and rail) are the most common modes of hazmat transportation. In 2012, highway accounted for 59.4% of the total tonnage (31.4 % of the total ton-miles) and rail constituted 4.3% of the total tonnage (27.6% of the total ton-miles) of hazmat transportation in the U.S. (U.S. Department of Transportation and U.S. Department of Commerce 2015) (Figure 1.1). Also, according to Pipeline and Hazardous Materials Safety Administration's (PHMSA) 2008-2017 ten-year incident summary reports (Pipeline and Hazardous Materials Safety Administration (PHMSA) 2018), hazmat-released highway incidents made up 87.6% of the total reported release incidents, 93.1% of fatalities, 72.2% of injuries, and 72.2% of the total damages (excluding pipelines). These values were 4.0%, 2.0%, 21.1% and 26.5% for rail incidents Figure 1.2). This information shows the importance of improving safe transportation of hazmat by trucks and trains.



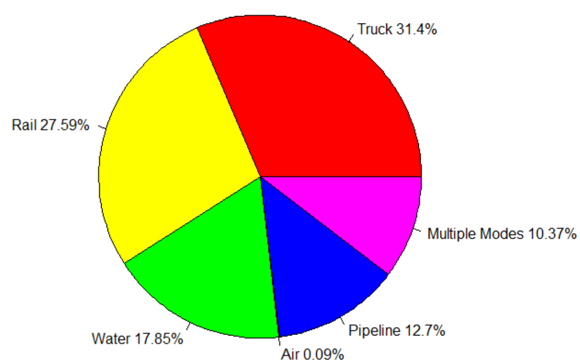


Figure 1.1 Distribution of Hazmat Transportation by Different Modes in the U.S. for Tons (left) and Ton-miles (right) of transportation (Source: 2012 Commodity Flow Survey)

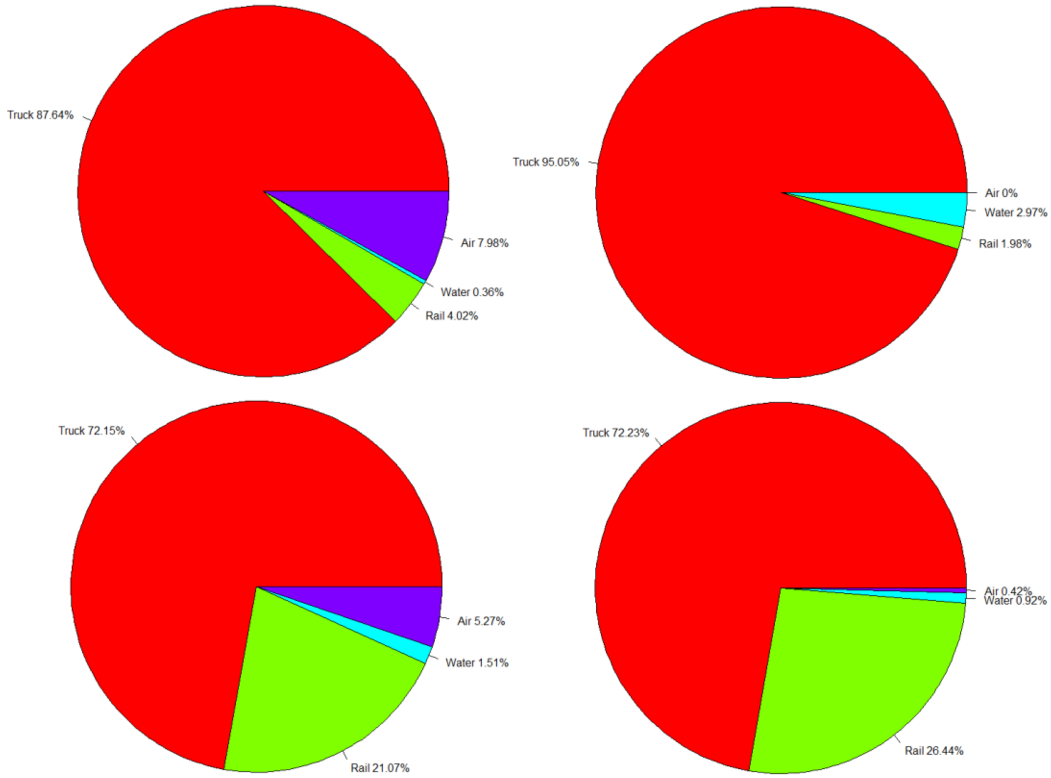


Figure 1.2 Distribution of Different Transportation Modes in Number of Hazmat Release Incidents (top left), Fatalities (Top Right), Injuries (Bottom Left) and Total Damages (Bottom Right) due to Hazmat Release Incidents (Source: 2008-2017 PHMSA ten-year incident summary reports)

1.2 Problem Statement

This research is focused on safe transportation of hazmat by trucks and trains at microscopic and macroscopic study levels, and from safety planning and shipper/carrier points of views. Transportation of hazmat exposes society to the costly consequences of release of hazmat when incidents happen. Therefore, stakeholders, such as safety planning agencies and hazmat shipper/carriers, are interested in decreasing these costs by reducing the likelihood and possible consequences of hazmat release during transportation. At both levels of study, the main objectives are: 1) identification and quantification of the effects of different factors on occurrence and consequences of hazmat-related incidents, towards identifying effective policies and countermeasures for improving safety and; 2) quantifying components of risk of hazmat transportation in a study unit (e.g. a link/route in a transportation network, an intersection, or a census tract) for costs prediction, planning purposes (e.g. hazmat network design), or short-term decision-making (e.g. routing).

1.3 Study Framework

In this study the major approaches of studying hazmat transportation and their objectives are categorized into microscopic and macroscopic levels. In the microscopic approaches, the unit of analysis is individual hazmat carrier incidents (e.g. trains, hazmat cars, or cargo tank trucks (CTTs)), and the potentially important variables are at microscopic-level (e.g. train length, tank car characteristics, or truck's weight). In the macroscopic approaches the unit of analysis is geographic areas, segments of transportation infrastructure, or pairs of origin-designation (OD). In these studies, the explanatory variables are at the macroscopic level (e.g. population, traffic volume, or volume of hazmat movement among ODs). Figure 1.3 presents the objectives and tools of this framework for hazmat transportation safety analysis.

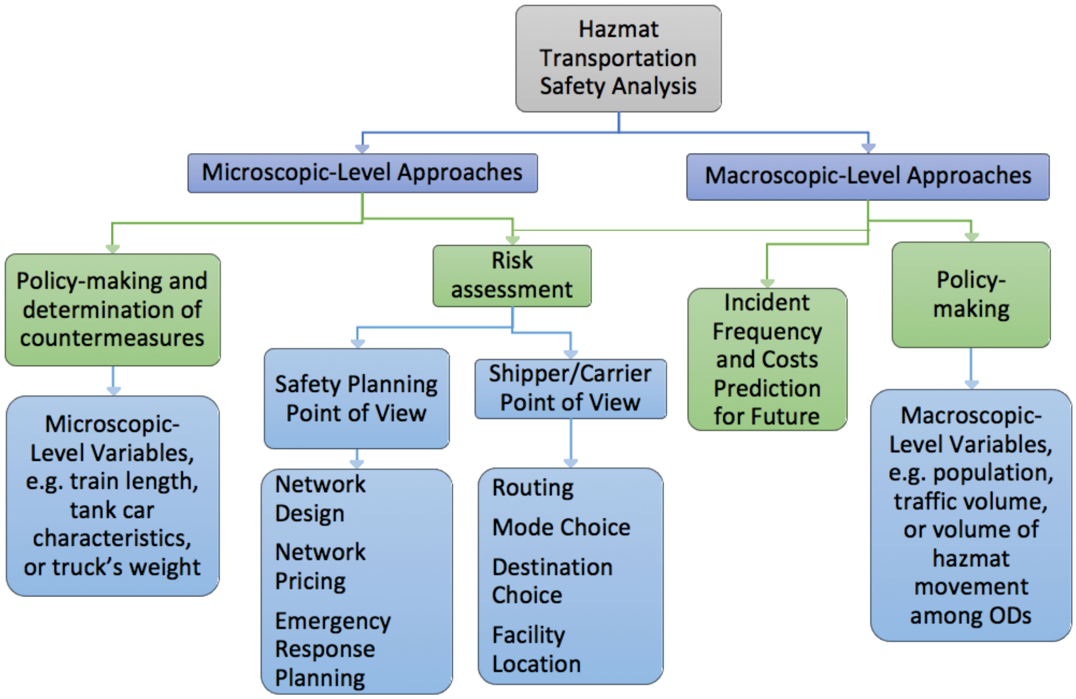


Figure 1.3 Outline of the objectives and tools for hazmat transportation safety analysis.

Microscopic and macroscopic analyses provide useful information for stakeholders and they can be used in risk-based decision frameworks. In this study, risk of hazmat transportation is defined as equation 1.1.

$$R_i = \pi_i c_i \tag{1.1}$$

In this equation, R_i is the risk of hazmat transportation on transportation entity i (a road segment, an intersection, a route, etc.), π_i is the probability of release of hazmat from train/truck on entity i, and c_i is the cost of release of hazmat from train/truck on entity i. Depending on the type of study, an appropriate entity may be chosen. For example, network design problems are usually formulated as link-based, while routing problems may rely mostly on the hazmat transportation risk of routes.

Probability of release of hazmat and release costs are quantified using equations 1.2 and 1.3.

$$\pi_i = P_i(incident) \times P_i(release|incident) \tag{1.2}$$

$$c_i = \sum_{k \in S} cost_i(k) \tag{1.3}$$

In these equations $P_i(incident)$ is the probability of occurrence of an incident on entity *i* (examples of incidents are train derailments or truck traffic crashes), $P_i(release|incident)$ is the conditional probability of release given an incident on entity i, $cost_i(k)$ is the costs of type *k* as a result of hazmat release on entity *i*, and *S* is the set of all types of costs, *S* = {carrier damage, property damage, response, clean-up, injuries, fatalities, evacuation, transportation infrastructure closure}.

In the above formulation of the hazmat transportation risk, $P_i(incident)$ has a macroscopic nature (defined as the frequency/rate of incident occurrence), while $P_i(release|incident)$ and c_i can be studied in a microscopic scale. Microscopic and macroscopic levels are introduced next, as individual types of study and also components of risk.

1.3.1 Microscopic-Level Approach

The main objectives of this approach are: 1) Policy-making and determination of countermeasures regarding safe transportation of hazmat: this approach is able to identify and quantify the impacts of microscopic-level variables on different components of risk of hazmat transportation. Such information enables governmental agencies to make policies to restrict and guide shippers/carriers towards fewer and less severe hazmat release incidents, and also enables shippers/carriers directly to determine countermeasures that can make their operations safer and less costly. 2) Risk assessment: it involves calculation of probabilistic costs of hazmat transportation on segments of transportation network. Risk can be used in decision-making from both safety planning and shipper/carrier's points of view. Network design and pricing for hazmat transportation, and emergency response planning are examples of government's decision frameworks, while hazmat routing, mode choice, destination choice and facility location (in cases of existence of more than one alternative) are shipper/carrier's concerns.

1.3.1.1 Conditional Probability of Release

In this research, different approaches for estimating $P(release|incident)$ for trucks and trains are proposed. The concept behind these approaches is estimating the probability of release of hazmat in an incident involving a hazmat-carrying truck/train, based on explanatory variables such as characteristics of truck/train, roadway/railroad, incident, and environment. The differences in the proposed approaches are based on the level of analysis, modeling techniques and how the variables are used. Different approaches for trucks and trains are as follows.

The conditional probability of release of hazmat from trains can be analyzed at train-level and hazmat car-level. In the former, the unit of analysis is trains and the probability of a train release is of concern, while in the latter hazmat cars are the units of analysis and a hazmat car release's probability is estimated. Equations 1.4 and 1.5 present these approaches, respectively.

$$P(release|incident)_{train} = \Phi(X_{train}, X_{railroad}, X_{environment}, X_{incident}) \quad (1.4)$$

$$P(release|incident)_{car} = \Phi(X_{car}, X_{railroad}, X_{environment}, X_{incident}) \quad (1.5)$$

In these equations, X shows the characteristics of its subscript. Some of the characteristics of incidents may depend on other explanatory variables (e.g. number of derailed/damaged cars may depend on train's speed) and can be estimated accordingly, while some of them are not predictable at the microscopic level (e.g. type of incident) and may be taken in to account in the estimation of $P_i(incident)$.

Conditional probability of release for hazmat-carrying vehicles, similar to trains, can be assumed to be a function of the explanatory variables (e.g. characteristics of trucks, road, environment, and crash). Equation 1.6 presents this approach.

$$P(release|incident) = \Phi(X_{truck}, X_{road}, X_{environment}, X_{crash}) \quad (1.6)$$

Examples for X_{crash} include number of vehicles involved in the crash and rolling over. According to literature (Douglas Behrens Pape 2012), in crashes of CTTs, one of the main highway hazmat carriers, rollovers are frequent, leading to hazmat release. While the number of vehicles involved in the crash is independent of the crash characteristics and may be predicted at the macroscopic level (similar to type of train incidents), rolling over can be modeled based on explanatory variables (similar to the number of railcars derailed/damaged).

1.3.1.2 Costs

Equation 1.3 showed that calculating costs of a hazmat release incident needs quantification of the eight members of set S. Each of these components are dependent on different factors, such as type of release (spillage and/or gas dispersion), consequences of release (fire, explosion, environmental damages, entering waterway), quantity of release, type of hazmat, mode of transportation, population living within a specified distance from the location of incident, public/private properties located within a specified distance from the location of incident, type of environment (e.g. type of soil), and distance to waterway. These factors are also interdependent, for example probability of fire depends on the quantity released, type of hazmat and type of release.

Quantification of some of these components can be based on statistical modeling. Equations 1.7 and 1.8 are examples of such approaches. It should be noted that, parameter estimation of these equations, along with the cost models, can provide useful information regarding policy- and decision-making.

$$P(fire|release) = \Phi(X_{hazmat}, X_{release}, X_{carrier,} X_{environment}) \quad (1.7)$$

$$P(explosion|release) = \Phi(X_{hazmat}, X_{release}, X_{carrier,} X_{environment}) \quad (1.8)$$

Examples for X_{hazmat} include type of hazmat, for $X_{release}$ include quantity released and type of release (spillage and/or gas dispersion), for $X_{carrier}$ include mode of transportation and their characteristics, and for $X_{environment}$ include weather. It should be noted that type of release is dependent on explanatory variables, itself and can be expressed as equation 1.9.

$$P(type\ of\ release|release) = \Phi(X_{hazmat}, X_{carrier,} X_{environment}) \quad (1.9)$$

1.3.2 Macroscopic-Level Approach

In the macroscopic-level approaches, the unit of study can be a geographic area (e.g. state, county, urban area), or pairs of ODs (e.g. among counties of a state). The main objectives of the macroscopic-level study of hazmat-related incidents are: 1) policy-making for decreasing hazmat transportation costs due to releases, by identifying and quantifying the macroscopic factors that affect these costs, such as hazmat production, consumption, infrastructure, policies and restrictions. 2) prediction of frequency and costs of hazmat transportation incidents in the future for planning, decision-making, and budget allocation.

1.3.2.1 Probability of Incident Occurrence

$P(incident)$ is commonly estimated as an annual incident frequency or rate (e.g. incidents per mile, incidents per ton-mile, or incidents per car-mile) multiplied by distance or the exposure measure of the transportation entity. Examples of such approaches can be found in (Harwood, Viner, and Russell 1990, 1993; Qiao, Keren, and Mannan 2009). Besides measures for traffic, incident rates are usually estimated based on characteristics of highway/rail, land-use characteristics and driving behavior. Incident frequency/rate can solely be the subject of a macroscopic study with the purpose of policy/countermeasure identification towards decreasing hazmat incident frequency/rates. An example is provided here to avoid confusion about the definitions of probability, frequency and rate in this context: if 5 derailments occur on a segment of a railroad per year and 3500 trains pass that segment every year, then: the frequency is 5 incidents per year; the rate of incidents is 5/3500 = 0.0014 crashes per train passage; if the traffic increases to 7000 trains in a year, we expect 7500*0.0014 = 10 crashes in that year; and the probability of a derailment in one passage of a train in that segment is 0.14%.

Area-based approaches may be used in macroscopic hazmat transportation safety analysis. However, in this research an OD-based macroscopic approach is considered. In this approach, frequency and costs of hazmat-related incidents among pairs of ODs in the area under study is modeled based on a set of macroscopic variables. The advantage of

OD-based approaches, as opposed to area-based approaches, is that variables such as hazmat traffic between the OD pairs, distance of transportation, and availability of modes of transportation can be taken into account. This approach can be formulated as equations 1.10 and 1.11.

$$freq_{ij} = \Phi(X_{hazmat\ traffic_{ij}}, X_{distance_{ij}}, X_{transportation\ infrstructure_{ij}}) \tag{1.10}$$

$$C_{ij} = \Phi(X_{hazmat\ traffic_{ij}}, X_{distance_{ij}}, X_{transportation\ infrstructure_{ij}}) \tag{1.11}$$

In these equations, $freq_{ij}$ and C_{ij} are frequency and costs of hazmat-related incidents between OD pair *i* and *j*, respectively and *X* represents different characteristics between OD pair *(i, j)*. The total costs of the area under study will be $\sum_i^n \sum_j^n C_{ij}$, in which *n* is the number of sub-areas.

1.4 Research Foci

Based on the study framework of section 1.3, previous studies (in chapter 2) and available data, six areas were identified as the foci for this dissertation.

The conditional probability of hazmat release from a hazmat-carrying train in a train incident or from a hazmat-carrying truck in a traffic crash is the subject of four of these foci. In the first focus, conditional hazmat release statistical models were estimated at train and car level for railroad incidents. The second focus estimated rollover and hazmat release statistical models for CTT crashes. In the third focus, crashes at highway-rail grade crossings (HRGCs) were analyzed and separate hazmat release statistical models were estimated for truck-train crashes where at least one of the two were carrying hazmat. The first three foci used statistical model-based approaches for modeling hazmat release with an emphasis on model interpretation for countermeasure and policy determination (while there was a minor emphasis on estimation of the release probability). The fourth focus used model-based and non-model-based classification and regression methods for classifying hazmat release and estimating hazmat release probability (along with a few other incident/crash outcomes) from trains and CTTs.

Transportation of crude oil by rail has increased significantly in the U.S. in the past decade. The other two foci of this dissertation (fifth and sixth) are on rail transportation of crude oil in the U.S. The fifth focus developed OD-based macroscopic-level statistical models to identify and quantify the effects of volumes and distances of crude oil movement and other macroscopic variables on the frequency and aggregate measures for severity of crude oil release incidents. The sixth focus identified and quantified the effects of crude oil, tank car and incident characteristics on types and consequences of crude oil release, using statistical models.

1.5 Dissertation Organization

This dissertation consists of ten chapters. Chapter 1 introduces the study background, states the research problem, outlines the study framework, lists the six foci of the dissertation and ends with introducing the structure of the manuscript. Chapter 2 presents a comprehensive literature review on the general topic of hazmat transportation safety. Chapter 3 introduces the statistical models and approaches that were used in this research. Chapter 4 to 9 each presents one of the six foci of the dissertation, including problem statement, methods, additional literature review, data description, modeling results and conclusions for each focus. Chapter 10 presents summary, general conclusions and recommendations for future studies.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

Safe transportation of hazmat has been a topic of research for decades. While the studies include a large variety of topics and approaches, in this literature review they are categorized into three major sets: studies that used operations research (optimization) as their main tool towards hazmat transportation safety operations; studies that are focused on assessment and quantification of risk of hazmat transportation; and studies that collected hazmat incident data from different sources and provided insightful descriptive statistics. This chapter presents general literature review, while chapters 4 to 9 present additional literature review wherever needed.

2.2 Operations Research

Operations research-based approaches have been used in the hazmat transportation literature, frequently. These approaches are proposed from both the safety planning and shipper/carrier points of view. Some of the methods from the safety planning point of view include: hazmat transportation network design (Verter and Kara 2008; Bianco, Caramia, and Giordani 2009; Erkut and Alp 2007; Kara and Verter 2004) which involves finding an optimum subset of the transportation network links to close down to the hazmat-carrying vehicles; transportation network pricing (Marcotte et al. 2009; Wang et al. 2012) that is the assignment of specific tolls to the transportation network links for the vehicles that carry hazmat; and emergency response planning (Hamouda 2004; Zografos and Androutsopoulos 2008) that includes decisions regarding location, routing and operations of emergency response units. Studies from the shipper/carrier’s point of view focus on: hazmat transportation routing (List et al. 1991; Abkowitz and Cheng 1988; Zografos and Androutsopoulos 2008; Romero, Nozick, and Xu 2016) which is the consideration of risk in routing caused by the hazmat on-board, besides the usual economic concerns in freight routing; mode choice (Bagheri, Verma, and Verter 2014) that involves the choice of the safest mode of transportation for hazmat; and facility location (Romero, Nozick, and Xu 2016), which is the identification of proper locations for hazmat storage, loading, unloading, etc.

Glickman et al. proposed a routing strategy for hazmat-carrying trains that accounts for incident risk from a macroscopic perspective. They quantified rail transportation risk by estimating the expected population that resides within a given radius of the location of a probable train incident and then used a weighted combination of cost and risk to generate alternate routes. The results showed in some cases the alternate routes achieved significantly lower risk measures than the practical routes at a small incremental cost (Glickman, Erkut, and Zschocke 2007).

Some studies focused on manifest trains (trains carrying both regular and hazmat freight). Verma presented a bi-objective optimization model for planning and managing railroad transportation of hazmat by determining the best routing plan for railcars, with hazmat and regular freight, and the number of trains of each type required to meet the given set of demand. The two minimization objectives were risk and costs (Verma 2009). Verma et al. also, proposed a bi-objective optimization problem for tactical planning of railroad hazmat transportation (short-term planning for a railroad company with predetermined amount of hazmat and regular freight to move). This formulation determines the routes to be utilized for each shipment, the yard activities, and the number of trains needed, while minimizing transportation cost and risk. Risk was defined based on population exposure (Verma, Verter, and Gendreau 2011).

Consistency between trucks and trains in intermodal hazmat transportation has been the subject of some studies. Verma and Verter defined rail–truck intermodal transportation of hazmat as inbound drayage (the transportation activity between the shipper and the origin rail terminal by truck), rail haul, and outbound drayage (between the destination rail terminal and the receiver by truck). They formulated a bi-objective optimization model to plan and manage intermodal shipments by minimizing transportation costs and population exposure to hazmat (Verma and Verter 2010). Assadipour et al. proposed a bi-objective optimization framework for planning rail–truck intermodal hazmat shipments, considering terminal equipment capacity and congestion. Risk and transportation costs were minimized, while satisfying the demand on-time. The results showed that congestion at the terminals is a potential source of public risk and could be a significant source if intermodal terminals are close to population centers. They proposed several approaches for reducing this congestion (Assadipour, Ke, and Verma 2015).

Some researchers used multi-objective optimization formulation of hazmat transportation to consider more than one aspect for optimality. Liu et al. formulated hazmat risk management as a multi-attribute decision analysis problem and estimated a negative binomial regression model to estimate car derailment probability, following the use of a pareto-optimality technique to determine the lowest risk that can be achieved at a specific level of investment. They analyzed two types of risk reduction strategies (broken rail prevention and tank car safety design enhancement) and their optimal combination under a budget constraint (Liu, Saat, and Barkan 2013). Zografos and Androutsopoulos presented a decision support system for hazmat routing considering travel time, risk and evacuation implications, while coordinating the emergency response deployment decisions with the hazmat routes. The proposed system worked towards alternative hazmat routing, in terms of cost and risk minimization, specification of locations for first-response emergency service units to achieve on-time response to accidents, and determination of evacuation paths from the impacted area to shelters (Zografos and Androutsopoulos 2008).

2.3 Risk Assessment

While quantifying risk of hazmat transportation for segments of the transportation systems is necessary in risk-based approaches to hazmat safety (such as in the operations research approaches mentioned earlier), it also may provide useful operational information. Risk of hazmat transportation is defined generally as the multiplication of probability of occurrence of an incident leading to hazmat release and a measure of consequences of such a release. Most of these definitions have some components in common and many studies focused on quantifying these components. Examples of these components include: hazmat-related incident rates in the transportation infrastructure (Anderson and Barkan 2004; Liu, Rapik Saat, and Barkan 2017); probability of release given an incident (Liu, Saat, and Barkan 2014; Treichel et al. 2006); and the release consequences (Saat et al. 2014; Liu et al. 2013).

A general study by Nayak et al. presented a set of methods for quantifying risk components in hazmat rail transportation. This included development of measures for accident rates based on track class, severity of an accident based on accident speed and the probability and mean amount of release based on accident speed. Finally, a method to estimate the impacts of hazmat release on people and property was proposed in this study (Nayak et al. 1983).

Incident rates per unit of transportation infrastructure (e.g. roadway segment, rail segment, route, etc.) as a component of hazmat transportation risk is studied. Harwood et al. calculated truck accident rates and hazmat-released truck accident probability based on a combination of federal and state truck accident databases. They found area type (urban/rural), roadway type (two-lane, multilane undivided/divided, and freeway), and truck ADT effective on accident rates, and type of incident (collision/non-collision, single/multiple vehicle, run-off/overturn, etc.) effective on hazmat release probability (Harwood, Viner, and Russell 1993). Qiao et al. developed hazmat transportation incident frequency models for trucks using negative binomial and fuzzy logic. The former was used to account for route-dependent variables (population, number of lanes, and weather) and the latter took into account route-independent variables (truck configuration, container capacity, and driver experience). They recommended the use of multiple data sources, such as The Department of Public Safety (DPS) accident databases and the Commodity Flow Survey (Qiao, Keren, and Mannan 2009).

Probability of hazmat release given a hazmat-carrying truck/train incident is another important component of hazmat transportation risk. Treichel et al. estimated probabilities of lading loss (given derailment) for a variety of tank car specifications, using logistic regression models. Head shield type, head thickness, tank insulation, shell thickness, tank car pressure and yard/mainline affected probability of release from head, shell, top fittings, and bottom fittings of tank cars. They also investigated effects of train speed on lading loss probability and the distribution of quantities of lading lost given a release (Treichel et al. 2006).

Another component of the hazmat transportation risk may be different measures for severity of incidents, which may be useful in predicting the consequences of release. One of these severity measures for trains is the number of released tank cars. Liu and Barkan estimated a generalized probabilistic model for the number of tank cars releasing hazardous materials in a train derailment. They considered train length, derailment speed, incident cause, position of the first car derailed, number and placement of tank cars in a train and tank car safety design as the potentially effective factors (Liu, Saat, and Barkan 2014). Liu and Hong estimated the number of tank cars released based on the number of tank cars derailed. They used a binomial model and a generalized binomial model. The former considers the probability of release from a tank car independent of the number of the other released tank cars, while the latter takes into account interdependence of released tank cars in a train incident. The results showed a better estimation by the generalized binomial model, indicating the presence of the interdependence (Liu and Hong 2015).

The number of released tank cars in an incident is a function of the number of derailed cars, as was shown in (Liu and Hong 2015). Therefore, some studies worked on modeling the number of derailed cars. Liu et al. used negative binomial models for the number of derailed tank cars based on track class, method of operation and annual traffic density. The latter variable was obtained from class 1 railroad companies, while the others were from the Federal Railroad Administration (FRA) data. Higher track classes, signaled operations and larger annual traffic density were associated with lower sizes of derailment (Liu, Rapik Saat, and Barkan 2017). Liu et al. analyzed derailments, as the most common type of freight-train accidents in the United States. Zero-truncated negative binomial regression model was developed to estimate the conditional mean of train derailment size. Recognizing that the mean is not the only statistic describing data distribution, a quantile regression model was also developed to estimate derailment size at different quantiles. Combining the two models resulted in a better understanding of train derailment severity distribution (Liu et al. 2013).

The consequences of release of hazmat and the subsequent costs is another major component of risk of hazmat transportation. These costs are comprised of carrier/property damage, response/clean-up costs, injuries/fatalities, environmental damages and evacuation. Some studies worked on quantifying these costs. Saat et al. proposed a quantitative environmental risk analysis of rail transportation for a group of chemicals. They developed probabilistic estimates of exposure to different spill scenarios. The authors considered the clean-up cost based on route-specific probability distributions of soil type and depth to groundwater, traffic volume, car accident rate, and car safety features (Saat et al. 2014). Dennis quantified the monetary costs of unit exposure of hazmat transportation by trains, considering type of hazmat based on environmental and safety hazard. The costs that were accounted for included equipment damage, lading loss, way and structures damage, signal damage, wrecking expenses, environmental costs, and others. The data was collected through a survey of railroads in the U.S. (Dennis 1996). Clark and Besterfield-Sacre proposed a data-driven quantitative risk assessment approach during unloading. They used latent class analysis, loglinear modeling and Bayesian networking as their data analysis tools. Consequences of hazmat release were considered as dollar loss and release quantity and the most influential variables on these two measures were related to the failure of the container (Clark and Besterfield-Sacre 2009).

Verma developed a risk assessment methodology for hazmat rail transportation based on the characteristics of trains and accidents, using Bayes Theorem and Logical Diagrams. The results of implementing the method on a case study found transportation risk a function of train length, train-decile position of the hazmat railcar, and the number of intermediate handling. The front of the train was found riskier, and that 7–9th train-deciles were the most appropriate for moving hazmat railcars for freight-trains of any length. Furthermore, it was concluded that rail-track risk can be reduced by strategically distributing hazmat railcars in the train-consist (Verma 2011).

2.4 Descriptive Statistics

Descriptive statistics could provide preliminary useful insight towards hazmat release incidents. Oggero et al. investigated 1932 incidents reported from the beginning of the 20th century to July 2004 around the world that involved the transportation of hazmat by road and rail. More than half of the incidents happened on roads (63%). The most frequent type of accidents were releases (78%), followed by fires (28%), explosions

(14%) and gas clouds (6%). More than half of the accidents did not cause any fatalities. Among fatal incidents the number of deaths was between 1 and 10, frequently. Given the occurrence of an incident, the consequences were more severe on average in train incidents, rather than trucks. Evacuations were rare, however the number of people evacuated was mostly between 101 and 1000 (29%), followed by the class of between 1 and 10 (24%) (Oggero et al. 2006). Ambituuni prepared descriptive statistics of 2318 accidents involving truck tankers carrying crude oil from 2007 to 2012 in Nigeria. The results showed 79% of the accidents were caused by human factors. More than 70% of the accidents resulted in loss of containment leading to spills, fires and explosions. 81% of the accidents resulted in either injuries, fatalities or both. About $7 million was estimated as the average cost per accident (Ambituuni, Amezaga, and Werner 2015).

2.5 Summary

Based on the literature review, areas that require more research attention are identified. Only one major study was found that focused on conditional probability of hazmat release given an incident (Treichel et al. 2006), which was a car-level modeling for trains. This probability needs to be studied at other levels considering more comprehensive variables for trains, and also for trucks. Hazmat-carrying CTTs' crash data is not analyzed sufficiently, based on this review, while they are responsible for a significant portion of hazmat release incidents in the U.S. Although a large number of studies focused on quantifying components of hazmat transportation risk, they rarely have evaluated the accuracy of these quantifications. While model-based statistical approaches are useful in measuring the impacts of factors on risk components, they may not be necessarily good predictors for these quantifications. So, non-model-based methods may provide better estimates, and this needs to be evaluated. Moreover, trucks and trains may involve in collisions in highway and railroad grade crossings (HRGC), leading to hazmat release, given either of them carrying hazmat. Such incidents are not investigated in the literature.

CHAPTER 3 METHODOLOGY

This chapter presents an introduction to the statistical models and other methods used in different sections of this research. While this chapter presents general information about each method, the way they are utilized, and necessary additional explanations are provided in chapters 4 through 9, as needed.

3.1 Logistic Regression and Multinomial Regression

Logistic regression models, a common method for modeling binary responses, are a type of Generalized Linear Models (GLMs) with the Bernoulli distribution assumption for the response variables and cumulative density function of a logistic probability function as the link function (Bilder and Loughin 2014; Agresti and Kateri 2011). Assuming outcomes of the binary response as success and failure, in logistic regression the probability of success (π_i) is modeled based a set of explanatory variables. In this study, π_i is the conditional probability of hazmat release in the i^{th} train incident or vehicle crash (hazmat release is replaced by other binary response variables in some sections of this dissertation). If $x_{i1}, \dots, x_{ip}$ are p explanatory variables measured on the i^{th} observation, in the logistic regression model π_i is defined as in equation 2.1.

$$\pi_i = \frac{\exp(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip})}{1 + \exp(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip})} \tag{2.1}$$

In this equation, $\beta_0, \dots, \beta_p$ are the logistic regression parameters or coefficients of the explanatory variables that are estimated based on the data. Equation 2.2 is another way to state logistic regression. The left side of equation 2.2 is the natural logarithm for the odds of success (hazmat release) and the right side is a linear combination of the coefficients with the explanatory variables, often referred to as linear predictors. This transformation of π_i is referred to as the logit transformation (Bilder and Loughin 2014).

$$log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} \tag{2.2}$$

In this study, Maximum Likelihood (ML), a common estimation approach for logistic regression, was replaced by the bias-reduction method developed by Firth (Firth 1993) (except where noted), as bias was detected in the outcome of ML estimation (abnormally large estimated standard errors for some of the coefficients (Bilder and Loughin 2014)). The bias could be due to complete or quasi separation (an explanatory variable separates the data between 0 and 1 for the response variable), as a result of rarity of cases of either outcome in the response variables.

In case of multi-category response variables (types and consequences of crude oil release in this dissertation), a popular model is multinomial regression (also known as multinomial logit model or baseline-category logit model), which is developed by selecting one response category as the base level and forming the odds of the remaining *J-1* categories against the base level (Bilder and Loughin 2014). Assuming category 1 as the base level, multinomial regression relates a set of explanatory variables to each log-odds by equation 2.3 for $j = 2, \dots, J$.

$$log\left(\frac{\pi_j}{\pi_1}\right) = \beta_{\mathrm{j}0} + \beta_{\mathrm{j}1} x_{i1} + \cdots + \beta_{jp} x_{ip} \tag{2.3}$$

The probabilities will then be defined as equations 2.4 and 2.5 for $j = 2, \dots, J$.

$$\pi_1 = \frac{1}{1 + \sum_{j=2}^{J} \exp(\beta_{\mathrm{j}0} + \beta_{\mathrm{j}1} x_{i1} + \cdots + \beta_{jp} x_{ip})} \tag{2.4}$$

$$\pi_j = \frac{\exp(\beta_{\mathrm{j}0} + \beta_{\mathrm{j}1} x_{i1} + \cdots + \beta_{jp} x_{ip})}{1 + \sum_{j=2}^{J} \exp(\beta_{\mathrm{j}0} + \beta_{\mathrm{j}1} x_{i1} + \cdots + \beta_{jp} x_{ip})} \tag{2.5}$$

Similar reasons, as in logistic regression, cause bias in ML estimates for multinomial regression. The bias-reduction method developed by Firth (Firth 1993) and adapted to the multinomial case by Kosmidis and Firth (Kosmidis and Firth 2011) is one solution for this issue and was utilized in this study due to detection of signs of bias in the ML-estimated models.

3.2 Mixed Logistic Regression

A logistic regression assumes uncorrelated observations in the dataset. However, single-level or multi-level grouping might exist in a dataset causing correlation among the observations. In the hazmat release models for trains, a single-level grouping existed in the train-level models, while a two-level grouping was present in the car-level models. Neglecting these correlations could result in smaller estimated variances, leading to model misinterpretation (Bilder and Loughin 2014). Generalized Linear Mixed Models (GLMMs) relax the uncorrelated observations assumption by inclusion of random effects in models. In case of this study, with binary response and Bernoulli distribution assumption, mixed logistic regression as a class of GLMM, were estimated. In a mixed logistic regression, equation 2.2 turns into equation 2.6. In this equation, b_{ji}s are the random parameters (for $j = 0$ to p) and are assumed to follow a normal distribution with mean of 0 and unknown variance (which will be estimated).

$$log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + b_{0i} + b_{1\mathrm{i}} x_{i1} + \cdots + b_{pi} x_{ip} \tag{2.6}$$

There are different methods for estimation of mixed logistic regression through ML, including penalized quasi-likelihood, Laplace approximation and Gaussian quadrature (Bilder and Loughin 2014). The latter one was used in this study.

3.3 Poisson Regression and Mixed-effects Negative Binomial Regression

Count-response models were estimated in several cases in this dissertation, including the number of railcars damaged/derailed on a train, the OD-based frequency of crude oil release incidents and the number of crude oil released tank cars. Poisson regression was an appropriate approach for the former case, while Mixed-effects Negative Binomial Regression was used in the other two.

For a count response variable Y_i and p explanatory variables $x_{i1}, \ldots, x_{ip}$ for the i^{th} observation, assuming a Poisson distribution with mean μ_i for Y_i, where $\mu_i = \exp(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip})$, results in the Poisson regression model. It is a GLM with Poisson random component, a linear systematic component $\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$ and logarithmic link function (Bilder and Loughin 2014). These models do not account for overdispersion, meaning there is more variability to the counts than what the models assume there is (Cox 1983). Negative Binomial Regression (NBR) (also known as negative binomial loglinear models) is often used as an alternative to the Poisson regression to account for overdispersion. NBRs assume a loglinear relation between the count response variable and the explanatory variables.

Let V_1, V_2, …, V_n denote an independent and identically distributed sample of unit mean gamma random variables with shape parameter α; that is $f(v_1) \propto v_1^{\alpha-1} e^{-\alpha v_1} I(v_1 > 0)$. Suppose the i^{th} count Y_i has a Poisson distribution with mean $v_i \mu_i$

conditional on v_i, therefore $Y_i|v_i \sim Poisson(v_i\mu_i)$. The counts are then marginally independent negative binomial variables with mass functions given by equation 2.7, where $y \in \{0, 1, 2, ...\}$ (Booth et al. 2003).

$$\Pr(Y_i = y; \alpha, \mu_i) = \frac{\Gamma(\mathrm{y} + \alpha)}{\Gamma(\alpha)y!}\left(\frac{\alpha}{\mu_i + \alpha}\right)^{\alpha}\left(\frac{\mu_i}{\mu_i + \alpha}\right)^{y} \tag{2.7}$$

If μ_i is related to a set of explanatory variables, denoted by vector $\boldsymbol{x}_i$, while β_0 and $\boldsymbol{\beta}$ are the model constant and the vector of model coefficients, respectively, the NBR loglinear equation will be as equation 2.8.

$$\log(\mu_i) = \beta_0 + \boldsymbol{x}_i{}'\boldsymbol{\beta} \text{ or } \mu_i = e^{\beta_0 + \boldsymbol{x}_i{}'\boldsymbol{\beta}} \tag{2.8}$$

Similar to the mixed logistic regression, a potential three-level correlation among the observations as a result of presence of grouping among them was possible. One way to account for this possible multilevel grouping was addition of random effects to the above NBR (Bilder and Loughin 2014; Booth et al. 2003), resulting in Mixed-effects Negative Binomial Regression (MNBR), as in equation 2.9.

$$\log(\mu_i) = \beta_0 + \boldsymbol{x}_i{}'\boldsymbol{\beta} + b_0 + \boldsymbol{x}_i{}'\boldsymbol{b} \text{ or } \mu_i = e^{\beta_0 + \boldsymbol{x}_i{}'\boldsymbol{\beta} + b_0 + \boldsymbol{x}_i{}'\boldsymbol{b}} \tag{2.9}$$

In this equation, b_0 is the random parameter for the model constant and it is assumed to have a Normal distribution with mean 0 and unknown variance. $\boldsymbol{b}$ is the vector of random parameters for some or all of the explanatory variables' coefficients, and they are also assumed to follow Normal distributions with mean 0 and unknown variances. These variances are estimated along with the fixed effects. Similar to mixed logistic regression, at least three methods are available for estimating MNBR through ML, and Gaussian quadrature was used in this study.

<u>3.4 Mixed-effects Ordered Logit Models</u>

As measures of aggregate severity of crude oil release incidents, quantity released and total costs of release of crude oil were categorized as ordinal categorical response variables. Ordered Logit Models (OLM), also known as cumulative logit models or proportional odds models, is a tool for modeling ordinal categorical response variables on a set of explanatory variables, through modeling cumulative probabilities based on the category ordering. If the probability of category i of the J categories of the response variable is π_i, then cumulative probability for category j of Y is $P(Y \leq j) = \pi_1 + \pi_2 + \cdots + \pi_j$ and $P(Y \leq J) = 1$. The log-odds of cumulative probabilities is, then, as equation 2.10 (Bilder and Loughin 2014).

$$\log\left(\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right) = \log\left(\frac{\pi_1 + \cdots + \pi_j}{\pi_{j+1} + \cdots + \pi_J}\right) \tag{2.10}$$

OLM assumes this log-odds of cumulative probabilities is a linear function of explanatory variables and also the slope of this relationship is the same regardless of the category j (Bilder and Loughin 2014; Agresti and Kateri 2011). The OLM model is stated as equation 2.11.

$$\log\left(\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right) = \beta_{j0} - \boldsymbol{x}_i{}'\boldsymbol{\beta} \tag{2.11}$$

In this equation, vector $\boldsymbol{x}_i$ is a set of explanatory variables, β_{j0} is the model constant for the response category j and $\boldsymbol{\beta}$ is the vector of model coefficients.

Similar to the MNBR model, to address grouping by inclusion of random effects in the OLM models, mixed-effects ordered logit models (MOLM) are used. Equation 2.12 shows MOLM. In this equation b_0 and $\boldsymbol{b}$ are defined as in equation 2.9 (Christensen 2011).

$$\log\left(\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right) = \beta_{j0} - \boldsymbol{x}_i'\boldsymbol{\beta} + b_0 - \boldsymbol{x_i}'\boldsymbol{b} \tag{2.12}$$

Among the three methods for ML estimation of MOLM (similar methods as in logistic regression and MNBR), Laplace approximation was used in this study.

3.5 Bayesian Model Averaging (BMA)

The idea behind BMA is to find an average for all the models, using different subsets of the set of explanatory variables which have close values of the variable selection criteria (instead of choosing one model as the best model) to account for the uncertainty in finding the best model (since a slight change in the data can result in selection of a different "best" model) (Bilder and Loughin 2014). Bayesian model averaging uses Bayesian theory to compute the probability that each possible model is the correct model (Hoeting et al. 1999).

Suppose *M* models are estimated, where *M* is the total number of possible models ($M = 2^p$). If Bayesian Information Criteria (a model selection criteria where lower values indicate better models) for model *m* is BIC_m, $m = 1, \dots, M$, the smallest value for *BIC* among all models is BIC_0, and $\Delta_m = BIC_m - BIC_0 \geq 0$, then assuming all models equally likely before estimation, the estimated probability that model *m* is correct, τ_m, is as equation 2.13.

$$\hat{\tau}_m = \frac{\exp(-\frac{1}{2}\Delta_m)}{\sum_{a=1}^{M}\exp(-\frac{1}{2}\Delta_m)} \tag{2.13}$$

If θ is the parameter being estimated, such as the logistic regression parameters, its estimate in model *m* is denoted by $\hat{\theta}_m$, and the corresponding variance is $\widehat{Var}(\hat{\theta}_m)$, then the model-averaged estimate of the parameter is as equation 2.14 and its variance is as in equation 2.15 (Bilder and Loughin 2014).

$$\hat{\theta}_{MA} = \sum_{m=1}^{M} \hat{\tau}_m \hat{\theta}_m \tag{2.14}$$

$$\widehat{Var}\left(\hat{\theta}_{MA}\right) = \sum_{m=1}^{M} \hat{\tau}_m [(\hat{\theta}_m - \hat{\theta}_{MA})^2 + \widehat{Var}(\hat{\theta}_m)] \tag{2.15}$$

Confidence intervals (CI) can be constructed for the model-averaged parameters based on $\hat{\theta}_{MA}$ and $\widehat{Var}\left(\hat{\theta}_{MA}\right)$. BMA results in non-zero estimates of all the parameters, but the explanatory variables that are truly unimportant are less likely to appear in models with high probability, so $\hat{\theta}_{MA}$ will be closer to 0 (Bilder and Loughin 2014). In this study, BMA was used in the CTT crash analysis. Also, Corrected Akaike Information Criteria (AICc) was used in the BMA procedure, instead of BIC, as AICc, relative to BIC, is inclined towards models with larger number of explanatory variables, which was desirable in this study.

3.6 Interpretation Tools for Statistical Models

Quantifying the effects of explanatory variables on response variables can be done in different ways, depending on the model and purpose. In this dissertation, Odds Ratios (OR) were used for binary, multi-category and ordinal response models, while Percentage Change (PC) was utilized for the count-response models.

Odds for binary response models is defined as the division of probability of hazmat release by probability of no release, in the conditional release models (similarly can be defined for other binary response variables, such as CTT rollover). For a *c*-unit increase in a continuous explanatory variable, x, equation 2.16 gives the odds ratio. The interpretation is that "the odds of hazmat release change by *OR* times for every *c*-unit increase in *x*, holding other variables constant". If *x* is a categorical explanatory variable, the value of *c* is 1, and the interpretation changes to "the odds of hazmat release change by *OR* times as *x* changes from 0 to 1, holding other variables constant" (Bilder and Loughin 2014).

$$OR = \frac{Odds_{x+c}}{Odds_x} = e^{c\beta_i} \tag{2.16}$$

PC is defined as the percentage change in the mean response that results from a *c*-unit change in an explanatory variable x_i (holding other explanatory variables constant) (Bilder and Loughin 2014). In MNBR, PC for x_i equals $100(e^{c\beta_i} - 1)$, if only the main effects of x_i is used in the model, and equals $100(e^{c\beta_i + c\beta_i{}' x_i} - 1)$, if the quadratic form of x_i is also in the model ($\beta_i{}'$ is the coefficient of the quadratic term). OR for MOLMs is defined as the change in the odds of $Y > j$ versus $Y \leq j$, corresponding to a *c*-unit change in an explanatory variable, x_i (also, holding other explanatory variables constant). Similarly, in case of inclusion of only the main effects of x_i, OR equals $e^{c\beta_i}$, and equals $e^{c\beta_i + c\beta_i{}' x_i}$, if the quadratic form is included.

3.7 Random Forests (RF)

RF is an ensemble machine learning method (methods that generate many classifiers/regressors and aggregate their results), proposed by Breiman (Breiman 2001). RF is based on bagging (bootstrap aggregating) with decision trees, meaning successive classification/regression trees are generated from data which do not depend on earlier trees (using a bootstrap sample of the training set), and the results of each classification/regression are aggregated as the final result (Breiman 2001; Friedman, Hastie, and Robert 2007). In RF, each node is split using the best among a subset of explanatory variables randomly chosen at that node. Performance of RF depends on tuning of the hyperparameters (parameters whose values should be set before training).

In this study, the hyperparameters included number of explanatory variables sampled randomly as candidates at each split (*v*), number of trees to generate (*t*), and terminal nodes' minimum size (*n*) (terminal nodes on decision trees are the nodes the algorithm do not split, and node size is the number of data observations associated with each node). RF was used as a classifier for hazmat release in train incidents and CTT crashes, and rollover for CTT crashes, and as a regressor for number of damaged/derailed railcars in a train incident. Due to data imbalance for classification in this study (the cases of hazmat release/rollover were significantly infrequent), RF was used with under-sampling. This means that the sample of the data for each tree is drawn with equal frequency of classes. Also, the hyperparameter tuning was based on out-of-bag samples (Friedman, Hastie, and Robert 2007).

3.8 Naïve Bayes

Naïve Bayes is a classification technique which is based on the Bayes' theorem and is appropriate when the number of explanatory variables is large. This method assumes that given a class for the response variable, the explanatory variables are independent (Friedman, Hastie, and Robert 2007). In other words:

$$\pi_i\left(j \middle| x_{i1}, \dots, x_{ip}\right) = \prod_{k=1}^{p} \pi_i(j|x_{ik}) \tag{2.17}$$

In this equation, $\pi_i\left(j \middle| x_{i1}, \dots, x_{ip}\right)$ is the probability of outcome *j* given the set of explanatory variables $x_{i1}, \dots, x_{ip}$, for observation *i*. The naïve Bayes classifier determines the classes based on the calculated $\pi_i\left(j \middle| x_{i1}, \dots, x_{ip}\right)$ using equation 2.18 for each observation and depending on the cutoff probability. Naïve Bayes was utilized as a classifier, for similar objectives as RF.

$$\pi_i\left(j \middle| x_{i1}, \dots, x_{ip}\right) = \frac{\pi_i\left(x_{i1}, \dots, x_{ip} \middle| j\right)\pi_i(j)}{\pi_i(x_{i1}, \dots, x_{ip})} \tag{2.18}$$

3.9 Support Vector Machines (SVM)

SVM is a machine learning approach, used for classification and regression, originally developed by Vapnik et al. (Boser, Guyon, and Vapnik 1992; Wu and Vapnik 1999). It is a system for efficiently training linear learning machines in the kernel-induced feature spaces, while respecting the insights provided by the generalization theory, and exploiting the optimization theory (Cristianini and Shawe-Taylor 2000). In this study, C-classification and ε-regression were used as the SVM setting for classification and count regression, respectively. A kernel function should be chosen to use in the structure of the algorithm, for which the Gaussian radial basis kernel was used in this study. This kernel function has a hyperparameter, γ, that should be tuned along with *c*, the cost of violation of the constraints of the optimization problem solved during training of SVM. Hyperparameter tuning for SVM in this study was based on 5-fold stratified cross validation. More in-depth information about SVM and stratified cross validation is available in (Friedman, Hastie, and Robert 2007). In this dissertation, SVM was used for the same objectives as RF.

3.10 Receiver Operating Characteristics (ROC) Curves and Cutoff Probabilities

ROC curves plot "sensitivity" (also known as "recall" in the classification evaluation) versus rate of "false positive (FP)" for various cutoff probabilities used with a classification method to choose a cutoff probability that corresponds to an appropriate level of sensitivity and FP rate. While these terms are explained in more details in the next section, in the context of ROC curves in this study, sensitivity was the proportion of actual cases of hazmat release (or other binary outcomes) correctly classified, while FP rate was actual non-release cases, incorrectly classified as release. The area under these curves (AUC) is a general criterion for performance evaluation in classification (Fawcett 2006).

3.11 Classification and Count Prediction Performance Evaluation Measures

The classification performance evaluation criteria in this study included confusion matrix, precision, recall (sensitivity), F_1 score and AUC (these measures were calculated for each method based on the test dataset). Confusion matrix summarizes the results of a classification method. For a binary classification with classes "negative" and "positive", the confusion matrix will be:

		Classified	
	Classes	-	+
Original	-	TN	FP
	+	FN	TP

In this matrix, *TN*, *FP*, *FN* and *TP* denote true negative, false positive, false negative and true positive, respectively. In the hazmat release classification, instead of negative and positive, the classes were “no release” and “release”, respectively. For example, *TN* is the number of no release crashes in the test dataset correctly classified as no release and *FN* is the number of release crashes incorrectly classified as no release. Precision, recall and F_1 score are defined as below:

$$Precision = \frac{TP}{TP + FP} \tag{2.19}$$

$$Recall = \frac{TP}{TP + FN} \tag{2.20}$$

$$\mathrm{F}_1\ Score = 2\frac{Precision \times Recall}{Precision + Recall} \tag{2.21}$$

In this study, recall is the proportion of real hazmat release cases that are correctly classified as hazmat release. Precision denotes the proportion of cases classified as hazmat release that are correctly hazmat release. Since cases with release of hazmat are significantly costlier than others, recall may be a better evaluation criterion in this study. However, precision may also provide useful information depending on how the estimated probabilities are to be used, as it captures the costs of misclassifying a non-release case as release. F_1 score is the harmonic average of precision and recall. These three criteria evaluate the performance of the classification after determination of the cutoff point, while AUC assesses the general classification regardless of the cutoff point.

This study used two measures for evaluating the prediction of number of damaged/derailed cars in a train, given an incident: Root Mean Square Error (RMSE), and Total Count Error (TCE). These measures are defined as below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\mu_i - y_i)^2}{n}} \tag{2.22}$$

$$TCE = \left|\frac{\sum_{i=1}^{n}\mu_i - \sum_{i=1}^{n}y_i}{\sum_{i=1}^{n}\mu_i}\right| \tag{2.23}$$

In the above equations, μ_i is the actual number of derailed or damaged cars in incident i, y_i is the predicted number of derailed or damaged cars in incident i, and *n* is the size of the test dataset. In case of this study, RMSE is more insightful relative to TCE, as the major use of the number of derailed/damaged cars prediction is using in the hazmat release models. In an independent usage where the number of derailed/damaged cars itself is of interest, TCE may be a more useful measure.

CHAPTER 4 TRAIN-LEVEL AND CAR-LEVEL MODELING OF HAZARDOUS MATERIALS RELEASE IN RAILROAD INCIDENTS

4.1 Introduction

Identification of operational, environmental, and technical factors affecting the probability of hazmat release from trains in railroad incidents is important for making decisions toward decreasing the probability of hazmat release in train incidents; it can also be useful in risk-based methods designed to improve the safety of rail transportation of hazmat.

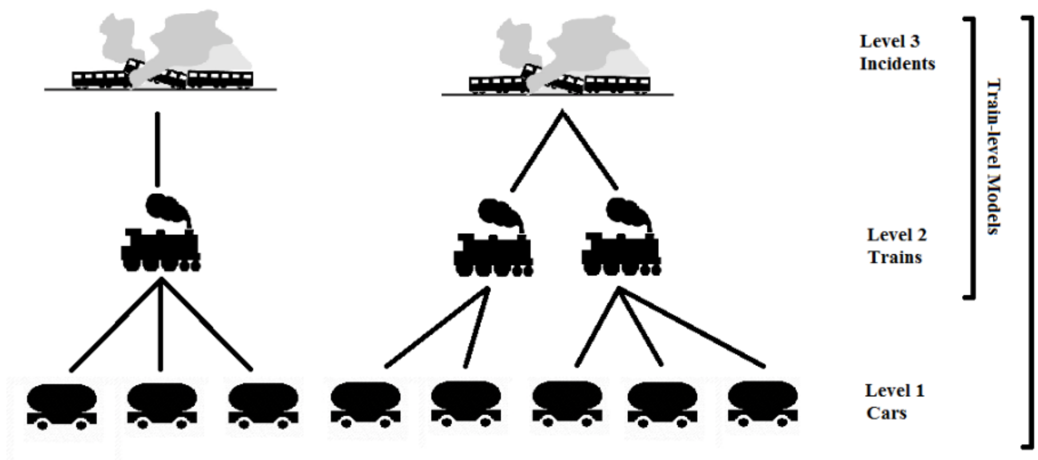
This chapter presents analysis of hazmat-carrying train incidents to fulfil two objectives: 1) quantifying the impacts of incident, railroad, environment and train/car characteristics on conditional probability of hazmat release (given a train incident) and 2) developing a prediction tool for this conditional probability. This chapter considered two sets of models; trains were the unit of analysis for the first set of models while hazmat cars were the unit of analysis for the second set. For both sets, logistic regression and mixed logistic regression were estimated using the Federal Railroad Administration (FRA) 2012-2016 rail equipment incident dataset. Single-level and two-level groupings in the train-level and hazmat car-level models (due to possible hazmat release interdependence among cars belonging to a train and trains belonging to an incident) were considered, and significant factors associated with hazmat release identified. Moreover, ROC curves were developed to improve the prediction performance of the models, by defining an appropriate cut-off point.

The next section explains the methods of this chapter. The ensuing section introduces the dataset and variables, followed by the estimation results of the models and interpretation. The last section presents the conclusions of this chapter.

4.2 Methods

As was mentioned in section 3.2, there is a possibility of interdependence in hazmat release from trains involved in an incident and hazmat cars that belong to a train, which may lead to a single-level correlation in the train-level models and a two-level correlation in the car-level models. Logistic regression does not consider multi-level correlation among observations, but mixed logistic regression has the capability of addressing it. Therefore, this study took both into account. As is shown in Figure 4.1, a single-level grouping existed in the train-level models while a two-level grouping was present in the car-level models. Neglecting these correlations might result in smaller estimated variances, leading to model misinterpretation (Bilder and Loughin 2014).

The response variable in the train-level logistic regression and mixed logistic regression models was a variable that indicated the occurrence of hazmat release from a train, given an incident. The response variable in the car-level logistic regression and mixed logistic regression models was the occurrence of hazmat release from a hazmat car (including tank cars, covered hoppers, gondolas, etc.), given an incident. The explanatory variables for the two sets of models included train/car, railroad, operation, environment and incident characteristics.



Note: Icons in this figure were obtained from http://iconfinder.com, http://clipartfest.com and http://thenounproject.com

Figure 4.1 Multi-level structure of the mixed logistic regression models.

The logistic regression and mixed logistic regression models can serve as prediction tools. As in section 3.10, ROC curves in this study aided visualizing, organizing and selecting prediction models based on their performance. In the context of this chapter, the definition of sensitivity was the proportion of actual incidents with hazmat release correctly predicted while the FP rate was actual incidents without hazmat release incorrectly predicted as hazmat release. Cut-off probabilities is the threshold for the estimated probabilities the model uses to predict “release” or “no release” for each incident. ROC curves plot sensitivity versus false positive rate for various cut-off probabilities used with a prediction model.

4.3 Data and Variables

Railroad reported incidents involving a hazmat-carrying train were extracted from the 2012-2016 US rail equipment incident database (Federal Railroad Adminsitration Office of Safety Analysis 2017). According to FRA: “*Rail equipment incidents are* *collisions, derailments, fires, explosions, acts of God, and other events involving the operation of on-track equipment (standing or moving) that result in damages higher than the current reporting threshold (i.e., $9,500 for calendar year 2012, $9,900 for calendar year 2013, $10,500 for calendar year 2014, $10,500 for calendar year 2015, $10,500 for calendar year 2016, and $10,700 for calendar years 2017 and beyond, until revised) to railroad on-track equipment, signals, tracks, track structures, or roadbed, including labor costs and the costs for acquiring new equipment and material.*" The extracted dataset consisted of 2581 incidents, 2787 trains, and 39162 hazmat cars. Car-level data was generated based on the original train-level dataset using information on number of hazmat-carrying cars, and number of cars that released hazmat. Tonnage of train cars was approximated by dividing the gross tonnage of trains (excluding the power units) by the number of cars in each train.

Table 4.1 and Table 4.2 present the variables of train-level and car-level datasets, respectively. Car-level models did not utilize train-level variables (e.g., *hazdamrate*, *derrate*, *typrr*, *tonnage*, and *hazcarrate*), since their possible impacts on hazmat release were at the train level; train-level models did not utilize the car-level variable *cartonnage*. All the categorical explanatory variables were used in the models as sets of dummy (indicator) variables, with the base level set to the first level (alphabetical order), with the exception of *typinc*, in which the third level (crossing incidents) was chosen as the base level. Track classes 1 and X were aggregated in one level for the variable *trkcls*, as they represented the same maximum speed for freight trains (10 mph). Also, track classes 5 to 9 were aggregated into one level (they were infrequent in the dataset).

Table 4.1 Statistics for Train-Level Variables

Variable	Variable Name	Values and Statistics
Response Variable		
Hazmat Release	hazrel	0 = No (96.73%), 1 = Yes (3.26%)
Explanatory Variables		
Incident Characteristics		
Type of incident	typinc	1 = Derailment (62.68%), 2 = Collision (12.77%), 3 = Crossing (8.50%), Others (16.04%)
Proportion of damaged/derailed hazmat cars to all hazmat cars	hazdamrate	Mean = 0.2504, Variance = 0.1540
Locomotive(s) derailed	locder	0 = No (91.96%), 1 = Yes (8.04%)
Proportion of damaged/derailed cars to all cars	derrate	Mean = 0.0989, Variance = 0.0331
Cause of incident	cause	E = Mechanical and Electrical Failures (12.16%), H = Human Factors (39.25%), M = Miscellaneous (20.99%), S= Signal and Communication (3.01%), T= Track, Roadbed and Structures (24.58%)
Railroad Characteristics		
Type of railroad (Interstate Commerce Commission)	typrr	1 = Class I (83.05%), 2 = Class II (0.90%), 3 = Class III (16.05%)
Method of operation	mopera	1 = Signal indication (24.26%), 2 = Direct train control (6.71%), 3 = Yard/restricted limits (2.08%), 4 = Block register territory (0.47%), 5 = Other than main track rules (66.49%)
Track class	trkcls	1 = Classes 1 and X (67.60%), 2 = Class 2 (7.61%), 3 = Class 3 (6.71%), 4 = Class 4 (14.46%), 5 = Classes 5 to 9 (3.62%)
Type of track	typtrk	1 = Main (32.44%), 2 = Yard (59.78%), 3 = Siding (2.37%), 4 = Industry (5.42%)
Environmental Characteristics		
Temperature	temp	Mean = 58.62, Variance = 496.55
Visibility	visibility	1 = Dawn (7.86%), 2 = Day (42.59%), 3 = Dusk (7.39%), 4 = Dark (42.16%)
Weather	weather	1 = Clear (66.49%), 2 = Cloudy (22.53%), 3 = Rain (7.14%), 4 = Fog (1.15%), 5 = Sleet (0.25%), 6 = Snow (2.44%)
Train Characteristics		
Train speed (mph)	trnspd	Mean = 12.37, Variance = 211.40
Train gross tonnage (ton)	tonnage	Mean = 4404, Variance = 21787396
Proportion of hazmat tank-cars to all tank-cars	hazcarrate	Mean = 0.2947, Variance = 0.0958
Remote control locomotive	rclmod	0 = No (80.19%), 1 = Yes (19.81%)

(Note: Data obtained from the FRA safety database (Federal Railroad Adminsitration Office of Safety Analysis 2017))

Table 4.2 Statistics for Hazmat Car-Level Variables

Variable	Variable Name	Values and Statistics
Response Variable		
Hazmat Release	hazrel	0 = No (99.38%), 1 = Yes (0.62%)
Explanatory Variables		
Incident Characteristics		
Type of Incident	typinc	1 = Derailment (67.46%), 2 = Collision (11.89%), 3 = Crossing (10.14%), Others (10.51%)
Locomotive(s) derailed	locder	0 = No (89.93%), 1 = Yes (10.07%)
Cause of incident	cause	E = Mechanical and Electrical Failures (14.38%), H = Human Factors (35.03%), M = Miscellaneous (20.01%), S= Signal and Communication (1.65%), T= Track, Roadbed and Structures (28.93%)
Railroad Characteristics		
Method of operation	mopera	1 = Signal indication (32.67%), 2 = Direct train control (8.25%), 3 = Yard/restricted limits (2.75%), 4 = Block register territory (0.60%), 5 = Other than main track rules (55.72%)
Track class	trkcls	1 = Classes 1 and X (57.83%), 2 = Class 2 (9.75%), 3 = Class 3 (10.03%), 4 = Class 4 (20.18%), 5 = Classes 5 to 9 (2.21%)
Type of track	typtrk	1 = Main (43.11%), 2 = Yard (48.92%), 3 = Siding (2.80%), 4 = Industry (5.17%)
Environmental Characteristics		
Temperature	temp	Mean = 57.30, Variance = 509.56
Visibility	visibility	1 = Dawn (8.15%), 2 = Day (43.68%), 3 = Dusk (6.81%), 4 = Dark (41.37%)
Weather	weather	1 = Clear (65.81%), 2 = Cloudy (22.60%), 3 = Rain (6.84%), 4 = Fog (2.06%), 5 = Sleet (0.25%), 6 = Snow (2.45%)
Train/Car Characteristics		
Train speed (mph)	trnspd	Mean = 13.89, Variance = 213.38
Tank car tonnage (ton)	cartonnage	Mean = 77.30, Variance = 5356.59
Remote control locomotive	rclmod	0 = No (88.37%), 1 = Yes (11.63%)

(Note: Data obtained from the FRA safety database (Federal Railroad Adminsitration Office of Safety Analysis 2017))

4.4 Modeling Results

This section presents the estimation results, model interpretations and prediction considerations.

4.4.1 Train-Level Models

This set of models provides the probability of hazmat release from one or more cars of each train, given an incident. The five binary response models (Table 4.3) include two logistic regression models estimated by ML (A1 and A2), one logistic regression model estimated by Firth's bias reduction estimator (FE) (A3), and two mixed logistic regression models (A4 and A5). The Likelihood Ratio (LR) test provided information on the impacts of each variable on probability of hazmat release, and variable selection (along with Akaike Information Criteria (AIC)). A comparison of models A2 and A3 shows a slight difference in the estimations, indicating possible biased estimation of A2; hence, A3 is preferable. The AIC values and the p-values of the LR test of the random parameters show that a mixed effects model is not necessary in train-level models. So, A3 was chosen as the best model for further interpretation (in terms of re-substitution validation, the performance of models was similar).

Table 4.3 Estimated Train-Level Models

Variables		A1) Logistic regression (ML)		A2) Logistic regression (ML)		A3) Logistic regression (FE)		A4) Mixed logistic regression		A5) Mixed logistic regression	
		LR test p-value		LR test p-value		LR test p-value		LR test p-value		LR test p-value	
typinc		0.01219	*	0.00778	**	0.00893	**	0.01219	*	0.00778	**
hazdamrate		0.00000	***	0.00000	***	0.00000	***	0.00000	***	0.00000	***
temp		0.79757		—		—		0.79757		—	
visibility		0.62895		—		—		0.62895		—	
weather		0.81558		—		—		0.81558		—	
trnspd		0.00003	***	0.00001	***	0.00001	***	0.00003	***	0.00001	***
tonnage		0.00470	**	0.00547	**	0.00564	**	0.00470	**	0.00547	**
trkcls		0.01460	*	0.01326	*	0.01483	*	0.01460	*	0.01326	*
typtrk		0.56286		—		—		0.56286		—	
locder		0.88518		—		—		0.88518		—	
derrate		0.27772		—		—		0.27772		—	
hazcarrate		0.00000	***	0.00000	***	0.00000	***	0.00000	***	0.00000	***
cause		0.00040	***	0.00022	***	0.00026	***	0.00040	***	0.00022	***
typrr		0.95962		—		—		0.95962		—	
rclmod		0.12957		—		—		0.12957		—	
mopera		0.99563		0.03931	*	0.04360	*	0.99563		0.03931	*
Random Effects	Variables	NA		NA		NA		Intercept		Intercept	
	Variance	NA		NA		NA		0.00000		0.00000	
	Variance LR test comparison with	NA		NA		NA		Model A1		Model A2	
	Variance LR test p-value	NA		NA		NA		0.49962		0.50000	
Re-substitution Validation	Release	20.88%		20.88%		20.88%		20.88%		20.88%	
	Overall	97.24%		97.00%		97.20%		97.24%		97.20%	
AIC		613.47		584.64		585.52		615.5		586.6	

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
NA: Not Applicable, — : Variable not used

Table 4.4 presents estimated coefficients and standard errors, the values of c for odds ratios, estimated odds ratios and 95% profile LR confidence intervals for odds ratios for model A3. The model interpretation is as follows (all the statements in the next two paragraphs are subject to “95% confidence” and “conditional on keeping all the other variables constant”):

Table 4.4 Estimated Coefficients and Odds Ratios for Model A3

Variables	Coefficients		Odds Ratios			
	Estimate	Std. Error	c	Point Estimate	Lower Bound of C.I.	Upper Bound of C.I.
(Intercept)	-8.6420	0.9631	NA	NA	NA	NA
typinc1	1.8090	0.5819	1	6.1055	1.9992	24.3916
typinc2	1.4260	0.7245	1	4.1634	0.9403	20.0359
typinc4	1.0590	0.6620	1	2.8822	0.7167	12.1323
hazdamrate	1.9220	0.3043	0.1	1.2119	1.1401	1.2955
trnspd	0.0515	0.0124	5	1.2934	1.1467	1.4924
tonnage	0.0001	0.0000	1000	1.0632	1.0207	1.1049
trkcls2	1.1100	0.4647	1	3.0346	1.1827	7.8901
trkcls3	1.0140	0.5390	1	2.7559	0.9264	8.3848
trkcls4	0.0606	0.6027	1	1.0625	0.2987	3.5781
trkcls5	0.2340	0.7896	1	1.2637	0.2241	5.9801
hazcarrate	2.5200	0.3450	0.1	1.2867	1.2016	1.3918
causeh	1.2340	0.5194	1	3.4358	1.2622	11.6063
causem	1.1060	0.5278	1	3.0208	1.0801	10.0642
causes	2.0230	0.7551	1	7.5599	1.3317	34.6251
casuet	1.7910	0.4570	1	5.9956	2.5679	18.7879
mopera2	-0.0712	0.3487	1	0.9313	0.4435	1.8342
mopera3	0.1922	0.6187	1	1.2119	0.279	3.8557
mopera4	0.4817	0.8202	1	1.6189	0.2403	7.2008
mopera5	-1.4510	0.5132	1	0.2343	0.0819	0.6649

NA: Not Applicable

Derailment incidents increased the odds of hazmat release by 2.0 to 24.4 times compared to a crossing incident, while sufficient evidence was not available to show that collisions and other types of incidents changed the odds of hazmat release, compared to crossing incidents. A 10% increase in the ratio of damaged or derailed cars resulted in 14% to 30% increase in the odds of hazmat release, and a 10% increase in the ratio of hazardous materials-carrying cars on a train increased these odds by 20% to 39%. A 5-mph increase in train speed was associated with 15% to 49% increase in the odds of hazmat release, and a 1000-ton increase in the gross tonnage of the train resulted in 2% to 11% increase in these odds.

FRA track class 2 increased the odds of hazmat release (given an incident) by 1.18 to 7.89 times, compared to FRA track class 1 and X. Other FRA track classes did not show statistically significant evidence of affecting the probability of hazmat release. Incidents due to track, roadbed and structures, signal and communication, human factors and miscellaneous causes compared to mechanical and electrical issues increased the odds of release by 2.57 to 18.79 times, 1.33 to 34.63 times, 1.26 to 11.61 times, and 1.08 to 10.06 times, respectively.

4.4.2 Hazmat Car-Level Models

This set of five binary response models provides the probability of hazmat release from each hazmat car, given an incident. A number of cars carried hazmat on each train with some releasing hazmat, leading to a potential two-level grouping in the dataset: hazmat cars belonging to the same train; and hazmat cars that belonged to the same incident from the same or different trains.

Table 4.5 presents the five estimated models including two logistic regression models with ML (B1 and B2), two single-level mixed logistic regression models (B3 and B5) with different explanatory variables and a 2-level mixed logistic regression (B4) to account for the two possible levels of grouping (there is no FE model as it was similar to the ML models).

AIC values and the LR test for variances of the random parameters in the mixed logistic regression models showed that grouping in the car level was statistically significant but the incident level grouping could be ignored. All mixed logistic regression showed the same cross validation performance and were superior to the logistic regression models; Model B5 was selected for interpretation.

Table 4.5 Estimated Hazmat Car-Level Models

Models		B1) Logistic regression (ML)		B2) Logistic regression (ML)		B3) Mixed logistic regression		B4) 2-level Mixed logistic regression		B5) Mixed logistic regression	
Variables		LR test p-value		LR test p-value		LR test p-value		LR test p-value		LR test p-value	
typinc		0.00000	***	0.00000	***	0.00033	***	0.00033	***	0.00055	***
temp		0.00000	***	0.00000	***	0.20616		0.20524		0.14155	
visibility		0.00002	***	0.00001	***	0.44398		0.44358		—	
weather		0.00804	**	0.00433	**	0.89123		0.89141		—	
trnspd		0.00000	***	0.00000	***	0.00000	***	0.00000	***	0.00000	***
cartonnage		0.12937		0.06547	.	0.89327		0.89327		—	
trkclas		0.00006	***	0.00000	***	0.06485	.	0.06488	.	0.00001	***
typtrk		0.87620		—		0.90482		0.90495		—	
locder		0.01132	*	0.00718	**	0.87437		0.87437		—	
cause		0.00000	***	0.00000	***	0.00000	***	0.00000	***	0.00000	***
rclmod		0.04997	*	—		0.04045	*	0.04040	*	0.10905	
mopera		0.38831		—		0.80503		0.80434		—	
Random Effects	Levels	NA		NA		1 Level (trains)		2 Levels (trains, incidents)		1 Level (trains)	
	Variables	NA		NA		Intercept		Intercept		Intercept	
	Variance	NA		NA		4.0200		(4.0140, 0.0000)		4.2820	
	Variance LR test comparison with	NA		NA		Model B1		Model B3		A logistic regression with similar variables	
	LRT p-value	NA		NA		0.00000	***	0.50000		0.00000	***
Re-substitution Validation	Release	0.00%		0.00%		4.98%		4.98%		4.98%	
	Overall	99.38%		99.38%		99.41%		99.41%		99.41%	
AIC		2356.5		2354.8		2101.3		2103.3		2080.3	

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
NA: Not Applicable
— : Variable not used

Table 4.6 presents odds ratios and their 95% profile LR confidence intervals for Model B5 along with estimated coefficients, standard errors and the values for the parameter *c*. All interpretations are subject to "95% confidence" and "conditional on keeping all the other variables constant". The model interpretation is as follows.

Table 4.6 Estimated Coefficients and Odds Ratios for Model B5

	Coefficients		Odds Ratios			
Variables	Estimate	Std. Error	c	Point Estimate	Lower Bound of C.I.	Upper Bound of C.I.
(Intercept)	-11.1806	0.9912	NA	NA	NA	NA
typinc1	2.3070	0.7003	1	10.0447	2.5459	39.6298
typinc2	2.0391	0.8566	1	7.6837	1.4335	41.1857
typinc4	2.0841	0.7568	1	8.0376	1.8235	35.4276
temp	-0.0071	0.0059	10	0.9317	0.8305	1.0452
trnspd	0.0593	0.0145	5	1.3451	1.1671	1.5502
trkcls2	1.6586	0.4454	1	5.2517	2.1937	12.573
trkcls3	1.4134	0.5152	1	4.1098	1.4973	11.281
trkcls4	0.5925	0.5848	1	1.8085	0.5748	5.6904
trkcls5	0.4597	0.9016	1	1.5836	0.2705	9.2701
causeh	1.5382	0.5839	1	4.656	1.4825	14.6227
causem	1.5662	0.6045	1	4.7885	1.4644	15.6576
causes	3.3066	0.8892	1	27.2922	4.7768	155.934
casuet	2.0961	0.5125	1	8.1344	2.9793	22.2088
rclmod	0.7857	0.4812	1	2.1939	0.8543	5.634

NA: Not Applicable

Derailment incidents, collisions and other types of incident increased the odds of hazmat release from a car by 2.55 to 39.63 times, 1.43 to 41.19 times and 1.82 to 35.43 times, respectively, compared to a crossing incident. The odds of release given an incident also increased by 17% to 55% for each 5-mph increase in train speed. FRA track classes 2 and 3 increased the odds of hazmat release by 2.19 to 12.57 times and 1.50 to 11.28 times compared to FRA tack class 1 and X, respectively. Incidents caused by track, roadbed and structures, signal and communication, human factors and miscellaneous compared to mechanical and electrical issues, increased the odds of release by amounts between 2.97 to 22.21 times, 4.78 to 155.93 times, 1.48 to 14.62 times, and 1.46 to 15.66 times, respectively.

4.4.3 Prediction

For both train-level and hazmat car-level models, the datasets were randomly divided to model estimation (80%) and model validation (20%) subsets. Models A3 and B5 were re-estimated using the estimation data subsets. Figure 4.2 presents the ROC curves for both models. The larger area under ROC curves showed that the car-level model provided better overall predictions.

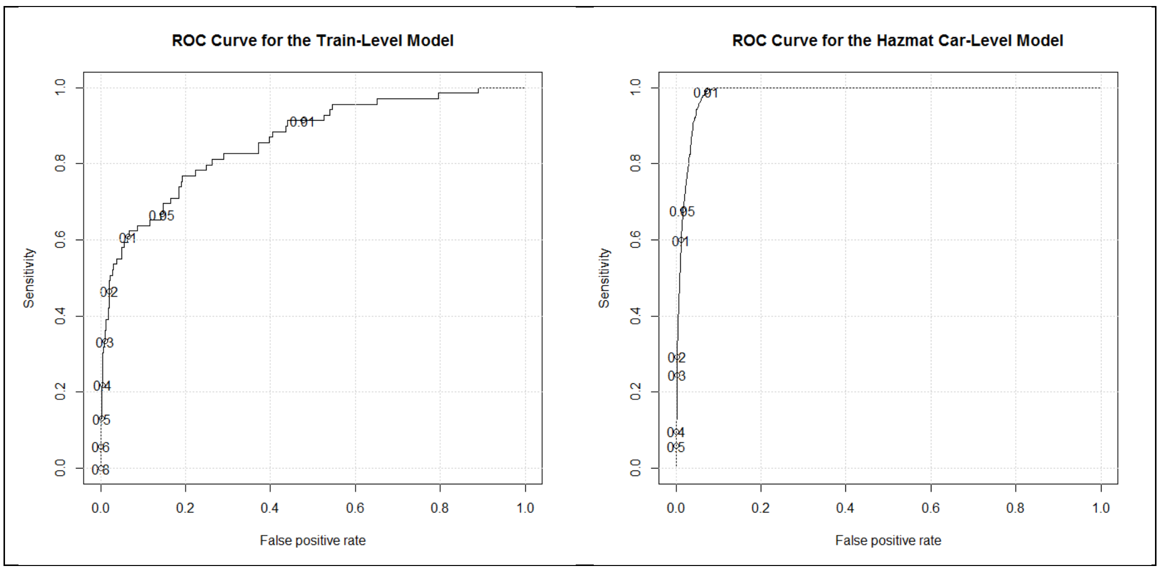


Figure 4.2 ROC curves for train-level and hazmat car-level models.

To achieve higher sensitivity without a large increase in false positive rates, using the ROC curves, new cutoff points were selected as 0.05 and 0.01 for the train-level and car-level models, respectively. The value of 0.05 relative to the default value of 0.5 corresponds to increase in sensitivity and false positive rate from 31.82% to 77.27% and from 0.19% to 14.77%, respectively, in the train-level model. These values for choosing

0.01 over 0.5 for the hazmat car-level model were from 3.85% to 78.85% and 0.01% to 7.38%, respectively. Table 4.7 shows the prediction results of both models for the validation subsets for the cutoff point of 0.5 and the new cutoff points of 0.05 and 0.01.

Table 4.7 Prediction Results of Train-Level and Hazmat Car-Level Models

	Train-Level Model				Hazmat Car-Level Model			
Cutoff Probability	0.5		0.05		0.5		0.01	
	No Release	Release	No Release	Release	No Release	Release	No Release	Release
No Release	534	1	456	79	7779	1	7206	574
Release	15	7	5	17	50	2	11	41
No Release	99.81%	0.19%	85.23%	14.77%	99.99%	0.01%	92.62%	7.38%
Release	68.18%	31.82%	22.73%	77.27%	96.15%	3.85%	21.15%	78.85%
Overall	97.13%		84.92%		99.35%		92.53%	

The results showed that both models with the new cutoff probabilities correctly predicted approximately 80% of hazmat release occurrences. However, the proportion of “no release” incidents predicted as “release” was twice as large for the train-level models. Overall, the new cutoff probabilities improved the prediction performance of the models, and the car-level models were preferred over train-level models.

4.5 Conclusions and Discussion

The research presented in this chapter showed that derailment type incidents increased the likelihood of hazmat release more than the other incident types. This finding strengthens the existing emphasis of researchers and policy-makers on preventing rail derailment incidents involving hazmat. Higher proportion of damaged/derailed hazmat cars in a train increased hazmat release probability, emphasizing the need and use of countermeasures aimed at decreasing the number of damaged/derailed cars in incidents. While all causes of incidents increased hazmat release probability, relative to the base level (mechanical and electrical failures), prioritization of the corresponding countermeasures and policies are suggested on this descending order: signal and communication; track, roadbed and structures; human factors; and miscellaneous.

Track class 2 in both models and track class 3 in the car-level models were associated with higher probability of hazmat release. This may be a consideration in routing of hazmat-carrying trains. In the train-level model, other than main track rules as a method of operation was associated with a decrease in hazmat release probability, relative to signal indication. Statistically significant evidence was not available with respect to the effects of environmental characteristics on hazmat release probability. These characteristics might have indirect effects captured in the model through other variables and may be assessed in a future study. Higher train speed, train gross tonnage and proportion of hazmat tank-cars on trains increased the hazmat release probability. These variables are useful in developing policies aimed at requiring railroad companies to decrease train speed, gross tonnage, and proportion of hazmat cars in hazmat-carrying trains.

The results of mixed models showed hazmat release from hazmat cars belonging to a train were interdependent and hazmat release from trains belonging to an incident were independent. Analyzing the incidents in train-level and car-level gave relatively consistent results. The train-level model accounted for variables such as *hazdamrate*, *derrate*, and *hazcarrate* leading to useful insights. The car-level model captured the effect of the number of cars released by having cars as units of analysis. Characteristics of hazmat cars were not available in the FRA dataset and therefore not considered in this study (which is a limitation of this study). In addition, the car-level model had better performance in prediction, suggesting the implementation of risk-based analyses at the car level.

As reported in the literature review, Liu et al. (Liu, Barkan, and Saat 2011) found track-related derailments more likely on lower class tracks. They also reported higher speed increased the average number of cars derailed in an incident, while Barkan et al. (Barkan, Dick, and Anderson 2003) reported that train speed increased the probability of hazmat release. These results are consistent with the findings of this study (reported herein). Barkan et al. (Barkan, Dick, and Anderson 2003) also identified the incident cause “broken rails or welds”, as the most significant incident cause on the number of derailed cars. Although, the current study accounted for grouped incident causes (due to limitations of the number of variables usable in the models), the group that contained this incident cause (Track, Roadbed and Structures) increased hazmat release probability, significantly. Other causes that were in the same group had different effects on release probability in (Barkan, Dick, and Anderson 2003), which could not be addressed in the current study.

The results and conclusions of this chapter may be biased to some degree because of exclusion of the explanatory variables that were not available in the data and probably were correlated to the explanatory variables that were included in modeling (this is also known as unobserved heterogeneity). This unavailability was due to either data collection restrictions or the fact that some potentially significant factors are not readily observable or practically impossible to collect. While inclusion of random parameters in the models of this chapter may have addressed this issue to some degree, in practice, the recommendations of this study based on its conclusions need to be taken into account cautiously (for policy- and decision-making), considering the fact that some of the observed effects of the explanatory variables may be fully or partially the actual effects of other unobserved factors.

Future research on this topic may investigate the effects of other variables, such as hazmat car specification and safety design, and type of hazmat on the hazmat release probability. The effects of incident causes on hazmat release at a more detailed level in train incidents can be the emphasis of a future study.

CHAPTER 5 ROLLOVER AND HAZARDOUS MATERIALS RELEASE MODELS FOR CARGO TANK TRUCK CRASHES

5.1 Introduction

CTTs are one of the major surface transportation carriers of hazmat. CTTs' rollover crashes are the leading cause of injuries and death from hazmat transportation incidents, accounting for approximately 75% of gasoline-related fatalities (Calabrese et al. 2017). CTTs are susceptible to rollover crashes due to their size, weight distribution, having a high center of gravity, and the surging and sloshing of the liquid cargo during transportation. Major strategies to address these rollovers are electronic stability control systems and driver training (National Highway Traffic Safety Administration (NHTSA) 2003; Calabrese et al. 2017; Douglas B Pape et al. 2007). Identification of factors that affect or associate with probability of rollover and hazmat release in CTT crashes is a step toward objectively reducing these probabilities.

The objectives of this chapter were identification and quantification of the effects of various factors on the probability of rollover and release of hazmat in CTT crashes and developing prediction tools for these two probabilities. Statistical modeling was performed using logistic regression and BMA with rollover and hazmat release as the binary response variables, and crash, trucks, roadway, environment, and driver characteristics as the explanatory variables. States of Nebraska and Kansas 2010-2016 police reported crash datasets were combined and filtered for CTT-involved crashes and used in the statistical modeling. ROC curves were developed for model validation and prediction performance evaluation and improvement. Statistical modeling provided useful information about the presence and magnitude of effects of explanatory variables on rollover and hazmat release. Based on the results, this chapter presents recommendations for countermeasures and policies toward improving safety of CTTs.

The remainder of this chapter includes: an additional literature review on safety aspects of CTTs; the chapter's methods; introduction to the dataset and variables; results of the statistical modeling; a discussion of the results; and finally, the chapter's conclusions.

5.2 Additional Literature Review

In addition to the general literature review of chapter 2 on hazmat transportation, this section reviews studies on safety aspects of CTTs.

Some studies focused on analysis of CTT-involved crash data. McKnight and Bahouth investigated 239 large truck rollover crashes in the US and found almost half of the crashes resulted from failing to adjust speed to curves, characteristics of the load, condition of the brakes, road surface, and intersection conditions. Other major crash contributors involved driver's attention, steering, and load size (McKnight and Bahouth 2009). Shen et al. studied 708 crashes of hazmat-carrying CTTs reported during 2004-2011 in China. They found the predominant crash types were rollover (29.10%), run-off-the-road (16.67%), and rear-end collisions (13.28%), with a high likelihood of hazmat release (up to 75.00 % for freeway crashes). Human-related errors (73.8%) and vehicle-related defects (19.6%) were the primary reasons of occurrence of such crashes (Shen et al. 2014).

Calabrese et al. analyzed 93 cargo tank rollovers (2011-2014) based on various elements focusing on potential human factors contributors. Driver related factors were most frequently identified contributing factors. Driver performance errors comprised about half of the rollovers, followed by driver decision errors. Analysis of ten-year historic crash statistics showed that the largest proportion of rollovers occurred on undivided roadways, straight roads without curves and away from intersections. The most effective countermeasures identified were stability control systems, lane departure warning, and driver monitoring technologies (Calabrese et al. 2017). Pape et al. evaluated different approaches to reducing CTT rollover and reported: motion-base simulators and driver performance monitoring systems could improve drivers' performance in avoiding rollovers; electronic stability aids could prevent rollovers by direct intervention in slowing the vehicle as it enters a curve at high speed; wider track width effective in avoiding rollovers; and sag and horizontal curve combination and pavement conditions as associated with tank trucks' rollovers (Douglas B Pape et al. 2008).

Some studies analyzed mechanical design of CTTs and their rollover potential. Kolaei et al. developed an analytical model of a partly-filled tank of arbitrary cross-section for predicting transient lateral slosh force and rollover moment. They suggested that a tank cross-section with lower overall center of mass and lower critical slosh length yielded an enhanced roll stability limit under medium- and high-fill conditions (Kolaei, Rakheja, and Richard 2014). Kang et al. formulated an optimization problem for finding optimal tank geometry to enhance roll stability limits of partial and fully loaded CTTs. They identified wider bottom tanks desirable for high fill volumes, while tanks with approximately conical geometry were desirable when fill volume varied considerably (X. Kang, Rakheja, and Stiharu 1999). Zheng et al. studied factors that influence driving stability of CTTs. They developed a vehicle dynamics model considering liquid sloshing during braking and turning for elliptical, circular and improved rectangular cross-section tank shapes and found that the latter tank shape had better driving stability, while the fill level of the liquid and the sloshing frequency of the tank influenced driving stability (Zheng et al. 2017).

As a summary, a number of studies worked on quantifying trucks' tank design features on rollovers by experimentation and simulation. A few studies quantified hazmat release probability from trains in train incidents. Although some studies used descriptive statistics (and not rigorous modeling techniques) in analyzing CTT crashes, the review of published literature did not uncover any studies specifically focused on identifying and quantifying the effects of the type of factors considered in this study on CTTs' rollover and hazmat release probabilities.

5.3 Methods

This chapter involves the estimation of statistical models for two outcomes of traffic crashes involving CTTs: rollover and hazmat release. These two binary variables (rollover/no rollover and hazmat release/no release) were the response variables modeled based a set of explanatory variables including characteristics of crashes, trucks, roadway, environment, and driver traits. The binary response models used were BMA-based logistic regression which combines logistic regression with BMA as an explanatory variable selection tool (introduced in section 3.5). This chapter utilized BMA-based logistic regression because: 1) availability of a relatively large set of explanatory variables made the task of variable selection for inclusion in the model specification more complicated thus requiring the use of a robust variable selection method and 2) this was an exploratory study and consideration of a model selection approach, such as BMA that does not eliminate variables from the models was desirable.

The BMA-based logistic regression models can serve as prediction (classification) tools for CTTs' rollover and hazmat release in crashes. In the context of this chapter, sensitivity was the proportion of actual crashes with rollover/hazmat release correctly classified, while FP rate was actual non-rollover/non-release crashes, incorrectly classified as rollover/release. Cutoff probability is the threshold for the estimated probabilities the model uses to classify outcomes: "rollover/release" or "no rollover/no release" for each crash.

5.4 Data and Variables

The 2010-2016 police-reported crash data from Nebraska and Kansas were combined and used in the statistical analysis. Other states in the Midwest were contacted but their data were unavailable in the timeframe for this study. The Nebraska and Kansas datasets were obtained from Nebraska Department of Transportation and Kansas Department of Transportation, respectively. Crashes with the involvement of CTTs were extracted from the combined dataset. This resulted in 2015 crashes with a CTT involved (all CTTs subset) and 546 crashes with a hazmat-carrying CTT involved (hazmat-carrying subset). The model for truck rollover used all the CTT-involved crashes (carrying hazmat or not), while the model for hazmat release used a subset of the data with hazmat-carrying trucks only. Besides rollover and hazmat release as response variables, this study utilized different characteristics of crash, CTTs, roadway, environment, and drivers as explanatory variables. Table 5.1 and Table 5.2 present these variables and their statistics in the CTT and hazmat-carrying CTT subsets, respectively.

Criteria for inclusion of the explanatory variables in the study were: 1) variables that were identified effective on different safety measures, e.g. injury severity, in the literature; 2) variables available in both Nebraska and Kansas crash data without significant ratio of missing values (while some information was collected differently in the two states, they were converted to a compatible format); and 3) variables that were identified potentially effective on probability of rollover and hazmat release in CTT crashes. Relative rarity of reported crashes with involvement of CTTs was the reason for using a larger crash interval (7 years), compared to usual crash data analyses.

Table 5.1 Descriptive Statistics for the CTT Crash Data

Variable	Values and Statistics
Response Variable	
Rollover	1 = No (84.57%), 2 = Yes (15.43%)
Explanatory Variables	
Crash Characteristics	
Vehicle Point of Impact	1 = None (3.08%), 2 = Center front (17.07%), 3 = Center rear (6.75%), 4 = Left front (10.87%), 5 = Left rear (5.66%), 6 = Left side (11.76%), 7 = Right front (14.29%), 8 = Right rear (5.26%), 9 = Right side (13.00%), 10 = All areas (0.99%), 11 = Other (11.27%)
Type of Crash	1 = Collision (86.60%), 2 = Non-collision (13.40%)
Object Involved	1 = No (81.24%), 2 = Yes (18.76%)
Vehicle Movement	1 = Straight (61.04%), 2 = Turning left (8.24%), 3 = Turning right (7.44%), 4 = Changing lanes (2.73%), 5 = Slowing/stopped in traffic (7.49%), 6 = Backing (2.68%), 7 = Other (10.37%)
CTT Characteristics	

Vehicle Body Style	1 = Single-unit (20.89%), 2 = Tractor & semi-trailer (71.71%), 3 = Tractor with doubles/triples (0.84%), 4 = Truck tractor (0.30%), 5 = Truck with trailer (6.25%)
Vehicle Make	1 = Freightliner (22.63%), 2 = Internat. Harvester (10.87%), 3 = Kenworth (19.90%), 4 = Mack (5.16%), 5 = Peterbilt (14.39%), 6 = Other (27.05%)
Vehicle Age	Mean = 7.55, SD = 6.62
Gross Vehicle Weight	1 = 10,000 lbs. or less (2.63%), 2 = 10,001 to 26,000 lbs. (9.33%), 3 = More than 26,000 lbs. (88.04%)
Roadway Characteristics	
Speed Limit	Mean = 53.73, SD = 15.05
Number of Lanes	1 = One (4.27%), 2 = Two (61.89%), 3 = Three (3.57%), 4 = Four or more (30.27%)
Road Surface Type	1 = Asphalt (55.78%), 2 = Concrete (35.38%), 3 = Dirt (1.84%), 4 = Gravel (6.50%), 5 = Other (0.50%)
Road Surface Condition	1 = Dry (82.03%), 2 = Ice (3.03%), 3 = Sand/mud (0.99%), 4 = Slush (0.15%), 5 = Snow (3.42%), 6 = Wet (9.23%), 7 = Other (1.14%)
Road Level	1 = Level (77.52%), 2 = Hilltop (1.89%), 3 = Slope (20.60%)
Road Curvature	1 = Straight (89.53%), 2 = Curved (10.47%)
Intersection Involved	1 = No (59.85%), 2 = Yes (40.15%)
Railroad Involved	1 = No (98.96%), 2 = Yes (1.04%)
In Workzone	1 = No (95.43%), 2 = Yes (4.57%)
Driver Characteristics	
Driver's Sex	1 = Male (98.06%), 2 = Female (1.94%)
Driver's Age	Mean = 47.55, SD = 12.94
Alcohol Related	1 = No (98.51%), 2 = Yes (1.49%)
Environmental Characteristics	
Weather Conditions	1 = Clear/Cloudy (86.15%), 2 = Blowing sand, soil, dirt, snow (1.34%), 3 = Fog, smog, smoke (1.49%), 4 = Rain/Sleet/… (0.10%), 5 = Severe crosswinds (6.80%), 6 = Snow (1.09%), 7 = Other (3.03%)
Light Conditions	1 = Daylight (73.50%), 2 = Dark (21.49%), 3 = Dawn/Dusk (5.01%)

(Note: Data obtained from Nebraska and Kansas Departments of Transportation)

Table 5.2 Descriptive Statistics for the Hazmat-Carrying CTT Crash Data

Variable	Values and Statistics

Response Variable	
Hazmat Release	1 = No (87.00%), 2 = Yes (13.00%)
Explanatory Variables	
Crash Characteristics	
Vehicle Point of Impact	1 = None (3.48%), 2 = Center front (17.58%), 3 = Center rear (6.78%), 4 = Left front (10.07%), 5 = Left rear (5.68%), 6 = Left side (12.27%), 7 = Right front (13.37%), 8 = Right rear (4.03%), 9 = Right side (14.10%), 10 = All areas (0.37%), 11 = Other (12.27%)
Type of Crash	1 = Collision (86.08%), 2 = Non-collision (13.92%)
Object Involved	1 = No (85.35%), 2 = Yes (14.65%)
Vehicle Movement	1 = Straight (62.09%), 2 = Turning left (7.14%), 3 = Turning right (7.14%), 4 = Changing lanes (1.83%), 5 = Slowing/stopped in traffic (8.06%), 6 = Backing (1.47%), 7 = Other (12.27%)
Rollover	1 = No (84.57%), 2 = Yes (15.43%)
CTT Characteristics	
Vehicle Body Style	1 = Single-unit (21.25%), 2 = Tractor & semi-trailer (69.41%), 3 = Tractor with doubles/triples (1.47%), 4 = Truck tractor (0.37%), 5 = Truck with trailer (7.51%)
Vehicle Make	1 = Freightliner (22.63%), 2 = Internat. Harvester (11.36%), 3 = Kenworth (24.73%), 4 = Mack (4.21%), 5 = Peterbilt (28.21%), 6 = Other (11.17%)
Vehicle Age	Mean = 6.30, SD = 5.30
Gross Vehicle Weight	1 = 10,000 lbs. or less (2.01%), 2 = 10,001 to 26,000 lbs. (5.13%), 3 = More than 26,000 lbs. (92.86%)
Roadway Characteristics	
Speed Limit	Mean = 54.86, SD = 14.46
Number of Lanes	1 = One (3.85%), 2 = Two (60.26%), 3 = Three (3.85%), 4 = Four or more (32.05%)
Road Surface Type	1 = Asphalt (56.04%), 2 = Concrete (34.98%), 3 = Dirt (1.83%), 4 = Gravel (6.41%), 5 = Other (0.73%)
Road Surface Condition	1 = Dry (81.32%), 2 = Ice (4.40%), 3 = Sand/mud (1.28%), 4 = Slush (0.18%), 5 = Snow (4.40%), 6 = Wet (7.88%), 7 = Other (0.55%)
Road Level	1 = Level (76.37%), 2 = Hilltop (1.47%), 3 = Slope (22.16%)
Road Curvature	1 = Straight (89.19%), 2 = Curved (10.81%)
Intersection Involved	1 = No (63.19%), 2 = Yes (36.81%)
Railroad Involved	1 = No (98.53%), 2 = Yes (1.47%)
In Workzone	1 = No (95.97%), 2 = Yes (4.03%)
Driver Characteristics	

Driver's Sex	1 = Male (98.90%), 2 = Female (1.10%)
Driver's Age	Mean = 48.76, SD = 11.92
Alcohol Related	1 = No (98.35%), 2 = Yes (1.65%)
Environmental Characteristics	
Weather Conditions	1 = Clear/Cloudy (86.81%), 2 = Blowing sand, soil, dirt, snow (1.10%), 3 = Fog, smog, smoke (0.73%), 4 = Rain/Sleet/… (6.59%), 5 = Severe crosswinds (0.92%), 6 = Snow (3.85%), 7 = Other (0.00%)
Light Conditions	1 = Daylight (72.89%), 2 = Dark (22.89%), 3 = Dawn/Dusk (4.21%)

(Note: Data obtained from Nebraska and Kansas Departments of Transportation)

5.5 Results

This section presents the results of the BMA-based models for CTTs’ rollover and hazmat release including the results and their interpretations of the statistical models regarding the effects of different factors on probability of rollover and hazmat release in CTT crashes. It also provides the ROC curves, cut-off probability determination and prediction performance evaluation of the estimated models.

5.5.1 Estimated Models

Table 5.3 and Table 5.4 present the BMA-based logistic regression models for rollover and hazmat release, respectively, in terms of estimated odds ratios and their 95% CIs. In these two tables, the variables are sorted based on their significance, according to the frequency of appearance in the estimated models with the highest AICc. Inclusion of “1.0” in a CI for an explanatory variable indicates a lack of sufficient statistical evidence for the effects of that explanatory variable on the response variable. The variables with sufficient statistical evidence towards their effects on the response variables are in bold fonts in these tables. Interpretation of the estimated odds ratios and CIs follows next. All the statements regarding the effects of each explanatory variable on the response variables are subject to 95% confidence while holding other explanatory variables in the model constant.

Table 5.3 Odds Ratios and 95% CIs for the Rollover Model

Variables		OR Point Estimate	95% Confidence Interval (CI)	
			Lower Bound	Upper Bound
Vehicle Point of Impact	Center front	1.99	0.46	8.71
	Center rear	0.47	0.07	3.33
	Left front	1.86	0.41	8.37
	Left rear	0.70	0.11	4.39
	Left side	3.69	0.84	16.13
	Right front	2.41	0.56	10.31
	Right rear	1.01	0.17	6.09
	Right side	**6.53**	**1.55**	**27.50**
	All areas	**45.06**	**4.86**	**417.62**
	Other	0.30	0.07	1.38
Type of Crash	**Non-collision**	**188.96**	**101.28**	**352.54**
Object Involved	**Yes**	**15.35**	**9.05**	**26.02**
Gross Vehicle Weight	**10,001 to 26,000 lbs.**	**12.53**	**1.42**	**110.47**
	More than 26,000 lbs.	**12.53**	**1.58**	**99.16**
Speed Limit (c = 5 mph)		**1.17**	**1.07**	**1.29**
Number of Lanes	Two	0.48	0.23	1.02
	Three	**0.01**	**0.00**	**0.21**
	Four or more	**0.22**	**0.09**	**0.55**
Vehicle Body Style	**Tractor & semi-trailer**	**0.59**	**0.36**	**0.98**
	Tractor with doubles/triples	1.01	0.11	9.12
	Truck tractor	11.39	0.39	329.44
	Truck with trailer	0.84	0.36	1.99
Vehicle Movement	Turning left	1.23	0.51	2.93
	Turning right	1.38	0.60	3.18
	Changing lanes	0.63	0.05	7.30
	Slowing/stopped in traffic	0.44	0.10	1.96
	Backing	**0.00**	**0.00**	**0.09**
	Other	**2.47**	**1.37**	**4.47**
Weather Condition	Blowing sand, soil, dirt, snow	0.09	0.00	1.56
	Fog, smog, smoke	0.39	0.08	1.86
	Rain/Sleet/...	0.83	0.28	2.45
	Severe crosswinds	**5.03**	**1.19**	**21.33**

	Snow	0.59	0.14	2.46
	Other	0.00	0.00	0.00
Light Condition	Dark	1.09	0.69	1.74
	Dawn/Dusk	**0.32**	**0.11**	**0.95**
Driver Sex	Male	0.84	0.24	2.98
Vehicle Make	Internat. Harvester	1.58	0.78	3.20
	Kenworth	0.55	0.28	1.06
	Mack	0.83	0.32	2.18
	Peterbilt	1.24	0.72	2.14
	Other	0.63	0.31	1.28
Road Surface Type	Concrete	0.73	0.43	1.25
	Dirt	**4.38**	**1.06**	**18.05**
	Gravel	1.91	0.91	3.98
	Other	1.57	0.24	10.19
Road Surface Condition	Ice	0.39	0.10	1.47
	Sand/Mud	**18.30**	**1.44**	**233.11**
	Slush	0.00	0.00	0.00
	Snow	1.08	0.34	3.45
	Wet	1.05	0.43	2.57
	Other	0.22	0.04	1.35
Driver Age		1.00	0.98	1.01
Road Level	Hilltop	1.21	0.42	3.46
	Slope	1.52	0.87	2.64
Alcohol Related	Yes	1.03	0.74	1.43
Intersection Involved	Yes	1.04	0.88	1.23
Railroad Involved	Yes	0.88	0.50	1.55
Truck Age		**1.00**	**1.00**	**1.01**
In Work Zone	Yes	1.00	0.93	1.07
Road Curvature	Curved	1.01	0.96	1.06

The odds of CTTs' rollover in a crash increased by an amount between 1.55 to 27.50 times when the point of impact was the right side of the truck, relative to when there is no impact. Also, in case of all areas of the truck being impacted, these odds increased by 4.86 to 417.62 times, relative to no impacts. The odds of rollover increased by an amount between 101.28 to 352.54 times in non-collision crashes, relative to collision crashes. Involvement of an object in crashes increased the rollover odds by 9.05

to 26.02 times. Gross truck weight groups of 10,001 to 260,000 lbs., and more than 26,000 lbs. increased the odds of rollover by amounts between 1.42 to 110.47, and 1.58 to 99.16, respectively, compared to trucks lighter than 10,001 lbs.

Each 5 mph increase in the posted speed, increased the odds of rollover of the CTTs in crashes by 7% to 29%. Relative to one lane, highways with three lanes, and highways with four or more than four lanes decreased the odds of rollover by 0.00 to 0.21 times, and 0.09 to 0.55 times, respectively. In terms of truck body style, tractor and semi-trailer decreased the odds of rollover, relative to single-unit trucks, by an amount between 0.36 to 0.98 times. Compared to moving straight ahead during a crash, backing decreased the odds of rollover by 0.00 to 0.09 times, while the movement group "Other" increased these odds by 1.37 to 4.47 times. Severe crosswinds, relative to clear weather increased the odds of rollover by 1.19 to 21.33 while light conditions during dawn/dusk, relative to daylight, decreased the odds of rollover by 0.11 to 0.95.

Dirt as the road surface type, compared to asphalt, increased the odds of truck rollover by 1.06 to 18.05 times, while sand/mud, as road surface condition, relative to dry surface, increased these odds by 1.44 to 233.11 times. Each year increase in the age of CTTs increased the odds of rollover by an amount up to 1%. The modeling effort did not uncover sufficient evidence toward the effects of other explanatory variables on the probability of CTT's rollover in crashes. Only two explanatory variables statistically significantly affected hazmat release from these trucks given a crash in a direct manner. Relative to non-rollover crashes, rollovers increased the odds of hazmat release by an amount between 8.22 to 29.27 times. When intersections were involved in a crash, the odds of hazmat release increased by 1.02 to 3.47 times.

Table 5.4 Odds Ratios and 95% CIs for the Hazmat Release Model

Variables		OR Point Estimate	95% Confidence Interval (CI)	
			Lower Bound	Upper Bound
Rollover	**Yes**	**15.51**	**8.22**	**29.27**
Gross Vehicle Weight	10,001 to 26,000 lbs.	1.70	0.17	16.56
	More than 26,000 lbs.	0.75	0.09	6.16
Intersection Involved	**Yes**	**1.89**	**1.02**	**3.47**
Truck Age		0.95	0.89	1.01
Object Involved	Yes	1.64	0.77	3.46
Speed Limit (c = 5 mph)		1.03	0.93	1.15
In Work Zone	Yes	0.84	0.36	1.96
Road Curvature	Curved	1.07	0.80	1.43
Alcohol Related	Yes	1.13	0.69	1.87
Vehicle Body Style	Tractor & semi-trailer	1.02	0.91	1.15
	Tractor with doubles/triples	1.13	0.69	1.84
	Truck tractor	0.00	0.00	Inf.
	Truck with trailer	1.00	0.90	1.11
Type of Crash	Non-collision	0.99	0.93	1.06
Light Condition	Dark	0.99	0.96	1.03
	Dawn/Dusk	1.02	0.92	1.13
Number of Lanes	Two	1.00	0.96	1.04
	Three	1.01	0.93	1.10
	Four or more	1.00	0.96	1.04
Road Level	Hilltop	1.00	0.95	1.04
	Slope	1.00	0.98	1.02
Vehicle Make	Internat. Harvester	1.01	0.96	1.06
	Kenworth	1.00	0.97	1.04
	Mack	1.01	0.95	1.08
	Peterbilt	1.00	0.98	1.02
	Other	1.02	0.94	1.12
Driver Sex	Male	0.99	0.94	1.05
Driver Age		1.00	1.00	1.00
Road Surface Condition	Ice	1.00	0.99	1.01
	Sand/Mud	1.00	0.98	1.01
	Slush	0.00	0.00	Inf.

	Snow	1.00	1.00	1.00
	Wet	1.00	1.00	1.00
	Other	1.00	0.99	1.01
Railroad Involved	Yes	1.00	1.00	1.00
Vehicle Movement	Turning left	1.00	1.00	1.00
	Turning right	1.00	1.00	1.00
	Changing lanes	1.00	1.00	1.00
	Slowing/stopped in traffic	1.00	1.00	1.00
	Backing	1.00	1.00	1.00
	Other	1.00	1.00	1.00
Weather Condition	Blowing sand, soil, dirt, snow	1.00	1.00	1.00
	Fog, smog, smoke	1.00	1.00	1.00
	Rain/Sleet/...	1.00	1.00	1.00
	Severe crosswinds	1.00	1.00	1.00
	Snow	1.00	1.00	1.00
Road Surface Type	Concrete	1.00	1.00	1.00
	Dirt	1.00	1.00	1.00
	Gravel	1.00	1.00	1.00
	Other	1.00	1.00	1.00
Vehicle Point of Impact	Center front	1.00	1.00	1.00
	Center rear	1.00	1.00	1.00
	Left front	1.00	1.00	1.00
	Left rear	1.00	1.00	1.00
	Left side	1.00	1.00	1.00
	Right front	1.00	1.00	1.00
	Right rear	1.00	1.00	1.00
	Right side	1.00	1.00	1.00
	All areas	Inf.	0.00	Inf.
	Other	1.00	1.00	1.00

5.5.2 Prediction

For both BMA-based logistic regression models (rollover and hazmat release), the datasets were split into two model estimation (80%) and model validation (20%) subsets. The splitting was stratified and random, meaning observations were randomly selected to be put in each subset, while the ratio of the classes (rollover/no rollover or release/no release) in each subset was held equal to the original data. This was to avoid conclusions that could vary due to randomness of the splitting, as the response variables' classes were highly imbalanced (positive outcomes were rare). Both models were re-estimated using the estimation subsets, validated using the validation subsets, and ROC curves were generated as in Figure 5.1. The area under the curves indicates that the rollover model did a better job in terms of prediction. Despite having a low rate of variables that statistically significantly affect the response variable, the hazmat release model also had a relatively sufficient prediction performance.

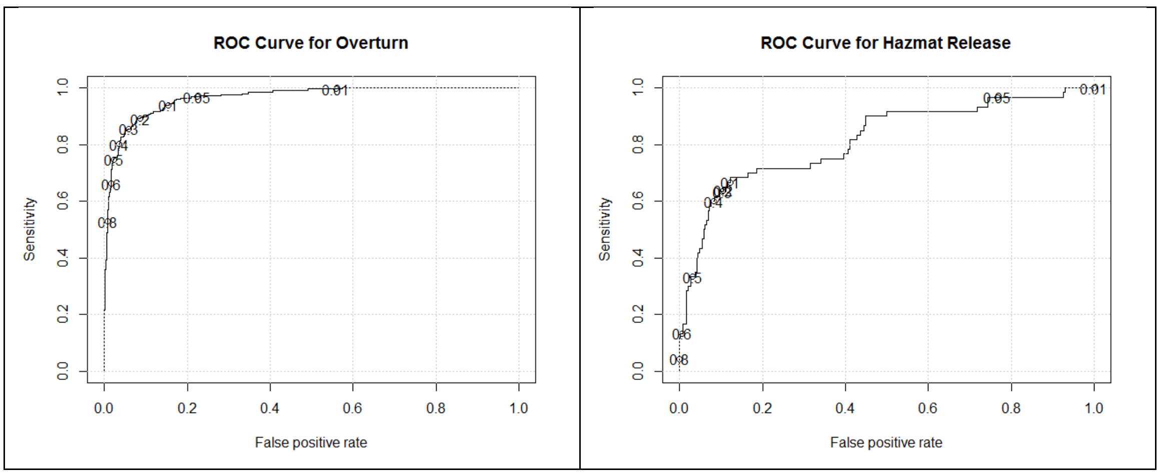


Figure 5.1 ROC curves for the rollover and hazmat release models.

Changing the cutoff probabilities based on the ROC curves can result in higher model sensitivity without a large increase in FP rates. For the rollover and hazmat release models, the new cutoff probabilities of 20% and 40% (instead of 50%), respectively, were determined. Table 5.5 shows the models' prediction performance for both sets of cutoff probabilities. Correct prediction of rollovers and hazmat release cases increased from 71% to 89%, and 45% to 64%, respectively, after using the alternative cutoff probabilities. These improvements are at the price of increase in FP rates from 4% and 5% in the rollover and hazmat release models, to 14% and 12%, respectively.

Table 5.5 Prediction Performance of the Models

	Rollover Model				Hazmat Release Model			
Cutoff Probability	0.5		0.2		0.5		0.4	
	No Rollover	Rollover	No Rollover	Rollover	No Release	Release	No Release	Release
No Rollover/Release	328	12	293	47	92	5	85	12
Rollover/Release	18	44	7	55	6	5	4	7
No Rollover/Release	96.47%	3.53%	86.18%	13.82%	94.85%	5.15%	87.63%	12.37%
Rollover/Release	29.03%	70.97%	11.29%	88.71%	54.55%	45.45%	36.36%	63.64%
Overall	92.54%		86.57%		89.91%		85.19%	

5.6 Discussion and Conclusions

A relatively large number of explanatory variables were found to affect or associate with the probability of CTTs' rollover in crashes. This justifies the use of BMA in this study. Only two explanatory variables, including rollover itself, influenced the probability of hazmat release. This indicates actions taken to avoid rollovers may affect hazmat release indirectly and in the same direction (if a change in the value of a variable decreases the probability of rollover, it decreases the probability of hazmat release as well).

Non-collision crashes were more probable to result in a rollover (representing only-rollover crashes). This finding emphasizes the possibility of the role of the other driver characteristics that were not included in this study (due to unavailability in the analyzed data). These characteristics, according to the literature, include inattention, and specific skills for driving CTTs in terms of speed adjustment, effective braking, and steering. In terms of point of impact, side impacts in addition to impacts to all areas of the vehicle, increases the likelihood of rollover, indicating it may be more effective if drivers of CTTs get trained towards avoiding such crashes.

Relative to moving straight ahead, the probability of rollover in a crash does not change for other types of movements (except backing), while one may expect turning movements may lead to rollovers more often. This finding is consistent with Federal Motor Carrier Safety Administration (FMCSA) CTT safety recommendations, where it is emphasized only 7% of CTTs' rollovers occur on exit ramps (Douglas B Pape et al. 2007). Backing crashes are less likely to lead into a rollover, probably due to lower speed and less severe collisions. Based on this finding, the roadway-related countermeasures for truck rollover and hazmat release are recommended to not be restricted to ramps.

Severe crosswinds was the only weather condition that increased the probability of rollover, relative to clear/cloudy weather. Such weather is suggested to be avoided by CTTs. This can be taken into consideration by policy-makers, private shippers, or truck drivers. If possible, driving during dawn and dusk and road surface conditions of sand and mud should be avoided. Probability of overturn increases when the CTTs are heavier (consistent with (National Highway Traffic Safety Administration (NHTSA) 2003)) and older. Probability of hazmat release increases when there is a rollover. Consequently, shippers are encouraged to consider newer trucks and also lighter trucks, in terms of truck type, body style and amount of loaded hazmat, specifically in cases of more dangerous classes of hazmat. The body style of tractor and semi-trailer decreases the probability of rollover, compared to all other body styles and is recommended to consideration, if practical.

Collision with objects increased the probability of CTT rollover. Guardrails and other roadside safety structures include a significant portion of these objects. Therefore, considering CTTs in the design of such structures, especially in the regions with higher traffic of CTTs, may be a reasonable approach for decreasing these rollovers. Only a 5-mph increase in the posted speed resulted in up to 27% increase in the odds of rollover of CTTs in crashes. Therefore, consideration of lower speed limits is recommended in areas with frequent passage of CTTs. In routing for CTTs, shippers may prioritize their options based on number of lanes (3 or more) and fewer intersections in addition to usual economic concerns, as higher number of lanes is associated with lower probability of overturn and intersections increase the odds of hazmat release.

Based on area under the ROC curves, both models had reliable prediction performances. Choosing alternative cutoff probabilities led to about 89% and 64% correct prediction of rollover and hazmat release cases. While this ensures the appropriateness of the models for inference on this crash data, these models can be utilized for prediction in risk-based hazmat transportation decision frameworks, such as routing, facility location, and network design. Besides hazmat release probability given a crash, these frameworks require quantification of other components of risk, e.g. CTT crash frequency, and consequences of hazmat release.

A limitation of this chapter was the geographic coverage of the analyzed data. A source for a national comprehensive police-reported crash data is not available, and each state keeps its own crash database, with different variables and not readily available to public. Although, Nebraska and Kansas, as two Midwestern states with relatively similar traits in terms of weather, roadways and driver behavior may provide results for the Midwest, the results may not be generalizable across the U.S. Another limitation was unavailability of some variables in the dataset that could potentially affect probabilities of rollover and hazmat release, such as more detailed driver and CTT characteristics, crash speed, type and amount of loaded hazmat, etc. (described as unobserved heterogeneity in chapter 4). This needs to be taken into account when implementing the policy- and decision-making recommendations of this chapter (the fact that some of the observed effects of the explanatory variables may be fully or partially the actual effects of other unobserved factors).

Future studies may address these limitations by using more comprehensive datasets and possible inclusion of missing information in this study's data. Utilizing other modeling methods and algorithms for inference and prediction may uncover additional useful information in future studies.

CHAPTER 6 MODELING THE PROBABILITY OF HAZARDOUS MATERIALS RELEASE AT HIGHWAY-RAIL GRADE CROSSINGS

6.1 Introduction

Trucks and trains carry substantial amount of hazmat in the U.S., leading to the potential of costly hazmat release incidents. While these incidents may occur anywhere on the transportation system, crashes at highway-rail grade crossings (HRGCs) may lead to hazmat release from either trucks or trains, or both. Identifying the contributing factors to hazmat release in HRGC crashes involving a hazmat-carrying truck or train is important for setting policies and for making more informed public safety-related decisions.

With a focus on crashes at HRGCs involving hazmat-carrying trucks and/or trains, the research objective of this chapter was to identify the effects of highway users' characteristics, truck/train attributes, environment, land-use and HRGC traits on the probability of hazmat release from trucks or trains in these crashes. The FRA's HRGC crash dataset (2007-2016) yielded two crash data subsets: 1) crashes involving hazmat-carrying trucks and 2) crashes involving hazmat-carrying trains. Logistic regression models were estimated using each data subset with hazmat release/no release as the response variable. Both models provided useful information about the presence and magnitude of effects of explanatory variables on hazmat release from these two transportation modes. Based on the results, this chapter presents recommendations for countermeasures and for policies toward decreasing hazmat release in HRGC crashes.

Organization of the remaining of this chapter is as follows. The next section presents an additional review of literature on safety of HRGCs. Methods, data and variables, and modeling results are the ensuing sections of this chapter. Discussion, conclusions and a list of references complete this chapter.

6.2 Additional Literature Review

In addition to the general literature review of chapter 2 on hazmat transportation, this section reviews studies on safety aspects of HRGCs.

The majority of studies on safety of HRGCs focused on analysis of crash frequency and severity at these transportation junctions. Raub examined the performance of four specific warning device classes (crossbucks only, STOP signs, flashing lights and gates) at HRGCs and compared their effects on crash frequency (Raub 2006). Hu et al. studied and identified factors associated with crash injury severity at HRGCs, which included number of daily trains, number of daily trucks, highway separation, an obstacle detection device, and approaching crossing marks (Hu, Li, and Lee 2010). Other factors that were associated with crash frequency and severity at HRGCs include highway motor vehicle driver's age and behavior, traffic volume, and weather conditions (Hao and Daniel 2013; Russo and others 2013). Zhao and Khattak found that greater number of highway lanes at HRGCs, the presence of standard flashing-light signals and clear weather decreased the likelihood of severe injuries (Shanshan Zhao and Khattak 2015). Zhao et al. showed that higher train speed, female pedestrians and commercial land use were associated with more severe injuries in pedestrian-train crashes at HRGCs (S. Zhao, Iranitalab, and Khattak 2018). Fan et al. identified pick-up trucks, concrete, and rubber surfaces associated with more severe crashes at HRGCs, while truck-trailers, snow and fog, and higher daily traffic volumes were more likely to be observed in less severe crashes (Fan, Kane, and Haile 2015).

The contributing factors to crash frequency and severity at HRGCs were relatively consistent in the reviewed studies. However, these results do not necessarily hold in describing probability of hazmat release, which warrants the investigation of hazmat-related crashes at HRGCs. The review of published literature did not uncover studies specifically focused on the safety of hazmat transportation at HRGCs by trucks and trains.

6.3 Methods

This chapter involved estimation of two logistic regression models for capturing possible impacts and associations of explanatory variables on the probability of hazmat release from hazmat-carrying trucks (Truck Model) and trains (Train Model) in crashes reported at HRGCs. Occurrences of hazmat release/no release from trucks and trains respectively were binary response variables in the two logistic regression models. Explanatory variables included HRGC-related traits, train and highway user characteristics, type of crash, and environmental and land-use characteristics.

6.4 Data and Variables

Ten-year U.S. HRGC accident/incident data (2007-2016) and HRGC history inventory data were obtained from FRA safety database (Federal Railroad Adminsitration Office of Safety Analysis 2017). According to FRA: "*Each HRGC accident/incident must be reported to the FRA, regardless of the extent of damages or whether a casualty* *occurred.*” Crashes were matched with the inventory dataset based on unique HRGC identification number and approximate date of crash. Two subsets of crashes were extracted from this dataset: 1) crashes with hazmat-carrying highway users (trucks) containing 75 crashes and 2) crashes with hazmat-carrying trains, including 3726 crashes. Truck Model and Train Model were estimated using these two subsets, respectively. Table 6.1 presents the variables and their statistics for the truck subset, while Table 6.2 shows similar information for the train subset.

Table 6.1 Variables and Statistics of the Hazmat-Carrying Truck Data Subset

Variable	Variable Name	Values and Statistics
Response Variable		
Hazmat Release	HAZREL	1 = No (45.33%), 2 = Yes (54.67%)
Explanatory Variables		
Highway User Characteristics		
Type of Vehicle	TYPVEH	1 = Truck (20.00%), 2 = Truck-trailer (72.00%), 3 = Pick-up Truck (08.00%)
Vehicle Speed	VEHSPD	Mean = 8.3467, Variance = 164.5268
Driver Age	DRIVAGE	Mean = 47.3467, Variance = 169.0944
Driver gender	DRIVGEN	1 = Male (98.67%), 2 = Female (1.33%)
Train Characteristics		
Railroad Class	TYPRR	1 = Class I (81.33%), 2 = Class II (01.33%), 3 = Class III (17.33%)
Freight Train	FREIGHT	1 = No (21.33%), 2 = Yes (78.67%)
Train Speed	TRNSPD	Mean = 32.4110, Variance = 326.5510
Number of Cars	NBRCARS	Mean = 51.5135, Variance = 1615.2670
Crash Characteristics		
Type of Crash	TYPACC	1 = Train Struck Highway User (92.00%), 2 = Train Struck by Highway User (08.00%)
Environment and Land-use Characteristics		
Temperature	TEMP	Mean = 63.1600, Variance = 473.4335
Weather	WEATHER	1 = Clear (64.00%), 2 = Cloudy (30.67%), 3 = Rain (05.33%), 4 = Fog, Sleet, Snow (00.00%)
Visibility	VISIBLTY	1 = Dawn (06.67%), 2 = Day (70.67%), 3 = Dusk (08.00%), 4 = Dark (14.67%)
Type of Land Use	DEVELTYPE	1 = Open Space (41.33%), 2 = Residential (09.33%), 3 = Commercial (10.67%), 4 = Industrial (30.67%), 5 = Other (08.00%)

HRGC Characteristics		
Cantilever Flashing-Light Signals	CANTALIVERFLS	1 = No (94.67%), 2 = Yes (05.33%)
Standard Flashing-Light Signals	STANDARDFLS	1 = No (69.33%), 2 = Yes (30.67%)
Bells	BELLS	1 = No (58.67%), 2 = Yes (41.33%)
Crossbucks	CROSSBUCKS	1 = No (32.00%), 2 = Yes (68.00%)
Gates	GATES	1 = No (70.67%), 2 = Yes (29.33%)
Highway Traffic Signal	HWYTRFICSIG	1 = No (98.67%), 2 = Yes (01.33%)
Audible	AUDIBLE	1 = No (80.00%), 2 = Yes (20.00%)
Stop Sign	STOPSIGNS	1 = No (64.00%), 2 = Yes (36.00%)
Other Control Devices	OTHER	1 = No (82.67%), 2 = Yes (17.33%)
Public/Private HRGC	PUBLIC	1 = No (29.33%), 2 = Yes (70.67%)

Table 6.2 Variables and Statistics of the Hazmat-Carrying Train Data Subset

Variable	**Variable Names**	**Values and Statistics**
Response Variable		
Hazmat Release	HAZREL	1 = No (99.86%), 2 = Yes (0.13%)
Explanatory Variables		
Highway User Characteristics		
Type of Vehicle	TYPVEH	1 = Auto (42.53%), 2 = Truck/Truck-trailer/Pick-up Truck (40.55%), 3 = Van/Bus/School Bus (03.43%), 4 = Pedestrian (04.85%), 5 = Motorcycle/Other (08.64%)
Vehicle Speed	VEHSPD	Mean = 7.2321, Variance = 128.9675
Driver Age	DRIVAGE	Mean = 42.3601, Variance = 299.6472
Driver gender	DRIVGEN	1 = Male (75.46%), 2 = Female (24.54%)
Train Characteristics		
Railroad Class	TYPRR	1 = Class I (86.23%), 2 = Class II (02.60%), 3 = Class III (11.16%)
Train Speed	TRNSPD	Mean = 32.7384, Variance = 243.8642
Number of Cars	NBRCARS	Mean = 69.1539, Variance = 1322.8460
Crash Characteristics		
Type of Crash	TYPACC	1 = Train Struck Highway User (82.54%), 2 = Train Struck by Highway User (17.46%)
Environment and Land-use Characteristics		
Temperature	TEMP	Mean = 60.8345, Variance = 491.5737
Weather	WEATHER	1 = Clear (69.78%), 2 = Cloudy (20.33%), 3 = Rain (05.60%), 4 = Fog, Sleet, Snow (04.29%)

Visibility	VISIBLTY	1 = Dawn (05.17%), 2 = Day (57.11%), 3 = Dusk (05.52%), 4 = Dark (23.18%)
Type of Land Use	DEVELTYPE	1 = Open Space (28.35%), 2 = Residential (21.08%), 3 = Commercial (26.79%), 4 = Industrial (16.30%), 5 = Other (07.48%)
HRGC Characteristics		
Cantilever Flashing-Light Signals	CANTALIVERFLS	1 = No (80.69%), 2 = Yes (19.31%)
Standard Flashing-Light Signals	STANDARDFLS	1 = No (54.30%), 2 = Yes (45.70%)
Bells	BELLS	1 = No (41.88%), 2 = Yes (58.12%)
Crossbucks	CROSSBUCKS	1 = No (32.00%), 2 = Yes (68.00%)
Gates	GATES	1 = No (70.67%), 2 = Yes (29.33%)
Highway Traffic Signal	HWYTRFICSIG	1 = No (97.61%), 2 = Yes (02.39%)
Audible	AUDIBLE	1 = No (63.88%), 2 = Yes (36.12%)
Stop Sign	STOPSIGNS	1 = No (78.98%), 2 = Yes (21.02%)
Other Control Devices	OTHER	1 = No (83.75%), 2 = Yes (16.25%)
Public/Private HRGC	PUBLIC	1 = No (12.82%), 2 = Yes (87.18%)

6.5 Modeling Results

Two logistic regression models were estimated for hazmat release from trucks (Truck Model) and trains (Train Model) in crashes at HRGCs. Variable selection was based on AICc. Some variables in both models were not statistically significant (at α = 0.10 level), but were retained in model specifications, since they contributed to the models according to AICc (via describing small proportions of variations in the response variable and affecting other parameters of the models) (Bilder and Loughin 2014). Table 6.3 shows the modeling results including estimated coefficients, standard errors, odds ratios and 90% profile likelihood ratio confidence intervals for odds ratios. The significance of estimated coefficients with 90% confidence can be judged by looking at the odds ratios' confidence intervals (if each interval does not contain 1, hypothesis of equality of the coefficient with zero is rejected).

In hazmat-carrying truck crashes at HRGCs, with 90% confidence and holding all the other variables constant except the variable being interpreted, presence of standard flashing-light signals decreased the odds of hazmat release from trucks by an amount between 0.0475 to 0.4716 times, relative to its absence. Railroad crossbucks decreased the odds of release from trucks by 0.0461 to 0.4065 times and public crossings increased these odds by 1.6148 to 15.8892 times, compared to private crossings. Railroad classes II and III decreased the odds of release from trucks by amounts between 0.0013 and 0.9781 and between 0.0496 and 0.4631, respectively, relative to railroad class I. Freight trains increased truck release odds by 1.9958 to 17.4551 times, compared to non-freight trains. Crossing control devices introduced as "Other Control Devices" (in Table 6.1) decreased the odds of release from trucks by 0.0907 to 0.8836 times, compared to absence of these control devices. Sufficient statistical evidence was not available to support the existence of effects of any other variables that were considered in this study on the release of hazmat from trucks in HRGC crashes.

In hazmat-carrying train crashes at HRGCs, again, with 90% confidence and holding all the other variables constant except the variable being interpreted, railroad class II increased the odds of hazmat release from trains by 1.3266 to 62.4336 times, relative to railroad class I. Railroad class III did not have any significant difference from railroad class I regarding the probability of hazmat release from trains. Type of highway user changed the probability of hazmat release from trains: trucks, truck-trailers and pick-up trucks increased the odds of release by an amount between 1.6463 to 57.1876 times, compared to automobiles; crashes with motorcycles, other motor vehicles and other objects increased these odds by 2.1248 to 112.5912 times, relative to automobiles; hazmat release probability did not change in crashes with vans, buses and school buses, and pedestrians relative to automobiles. An increase in temperature by 5^{o} F decreased the odds of hazmat release from trains by an amount between 0.7990 to 0.9863 times. Fog, sleet and snow increased the odds of release by 1.3229 to 24.0584 times, relative to clear weather. There was not enough statistical evidence toward the existence of any impacts or association of any other variables on the release of hazmat from trains in HRGC crashes.

Table 6.3 Results of Truck and Train Logistic Regression Models

Variable	c	Truck Model					Train Model				
		Estimated Coefficient	Standard Error	Odds Ratios	Odds Ratios 90% Confidence Interval		Estimated Coefficient	Standard Error	Odds Ratios	Odds Ratios 90% Confidence Interval	
					Lower Level	Upper Level				Lower Level	Upper Level
(Intercept)	NA	0.1276	0.6314	NA	NA	NA	-7.52731	1.44417	NA	NA	NA
TYPACC2	1	-1.5033	1.0194	0.2224	0.0409	1.0216	0.94787	0.66771	2.5802	0.8604	7.738
STANDARDFLS	1	-1.8406	0.7061	0.1587	0.0475	0.4716	—	—	—	—	—
CROSSBUCKS	1	-1.9297	0.6706	0.1452	0.0461	0.4065	—	—	—	—	—
PUBLIC	1	1.5747	0.7058	4.8294	1.6148	15.8892	—	—	—	—	—
TYPRR2	1	-2.6878	2.4092	0.0680	0.0013	0.9781	2.20836	1.17077	9.1008	1.3266	62.4336
TYPRR3	1	-1.8332	0.6919	0.1599	0.0496	0.4634	-0.84804	1.12983	0.4283	0.0668	2.7466
FREIGHT	1	1.7275	0.6682	5.6267	1.9958	17.4551	NA	NA	NA	NA	NA
OTHER	1	-1.2336	0.7053	0.2912	0.0907	0.8836	—	—	—	—	—
TYPVEH2	1	—	—	—	—	—	2.27244	1.07845	9.7031	1.6463	57.1876
TYPVEH3	1	—	—	—	—	—	2.32472	1.51188	10.2238	0.8503	122.9214
TYPVEH4	1	NA	NA	NA	NA	NA	2.31776	1.50243	10.1529	0.8577	120.1858
TYPVEH5	1	NA	NA	NA	NA	NA	2.73871	1.20683	15.467	2.1248	112.5912
TEMP	5	—	—	—	—	—	-0.02382	0.01281	0.8877	0.799	0.9863
WEATHER2	1	—	—	—	—	—	1.00773	0.68463	2.7394	0.8883	8.4473
WEATHER3	1	—	—	—	—	—	0.80258	1.16608	2.2313	0.3278	15.1896
WEATHER4	1	—	—	—	—	—	1.73017	0.88173	5.6416	1.3229	24.0584
DEVELTYPE2	1	—	—	—	—	—	-0.42363	1.22511	0.6547	0.0873	4.9111
DEVELTYPE3	1	—	—	—	—	—	0.42381	0.89897	1.5278	0.3482	6.7025
DEVELTYPE4	1	—	—	—	—	—	1.18478	0.84209	3.27	0.8185	13.0645
DEVELTYPE5	1	—	—	—	—	—	1.53165	0.97012	4.6258	0.9379	22.8138

—: Not Used in the final model, NA: Not Applicable

6.6 Discussion and Conclusions

Standard flashing-light signals, railroad crossbucks and "other crossing control devices" (as is in Table 6.1) were effective in reducing the probability of hazmat release from trucks in truck-train HRGC crashes. The use of such control devices is recommended at HRGCs with high hazmat-carrying truck traffic. Prioritization of safety countermeasures implementation may be given to public HRGCs since hazmat release is more probable at these locations relative to private crossings. Freight trains were associated with higher probability of hazmat release from trucks. This finding is reasonable as freight trains are usually longer and heavier relative to other (e.g., passenger) trains. HRGCs with more frequent passage of trains that belong to railroad classes II and III, and less frequent passage of freight trains were safer for hazmat-carrying trucks. Routes that minimize the interaction between these trucks with class I railroads and freight trains may be preferred and considered in the route selection of hazmat-carrying trucks.

Hazmat-carrying class II railroads were more vulnerable in HRGC crashes relative to class I railroads in terms of hazmat release. Extra train hazmat safety consideration is recommended for hazmat carrying trains on routes with HRGCs that carry high volumes of trucks, truck-trailers and pick-up trucks, and also motorcycle and other vehicles (relative to automobiles). With the exception of motorcycles, different types of trucks and other vehicles (e.g. recreational vehicles) are heavier than automobiles on average, leading to potentially more severe collisions and higher probability of hazmat release from trains. Since higher temperature and presence of fog, sleet and snow were associated with smaller and larger probability of hazmat release, respectively, weather considerations are recommended in shipping of hazmat by rail and may be used in relevant policy-making.

Both models may be used as a part of a risk assessment framework as explained in section 1.3. The framework may include at least two steps: models that predict the occurrence of crashes at HRGCs, based on variables such as highway and rail traffic, land use, control devices, etc. (e.g. (Oh, Washington, and Nam 2006; Yan, Richards, and Su 2010)); and models, such as those estimated in this study, that predict the probability of hazmat release from trucks, trains, or both, given the occurrence of a crash. The product of these two probabilities can provide a hazmat risk measure for each HRGC, useful to serve as a prioritization tool for countermeasure implementation or resource allocation.

As was mentioned in the literature review, a significant number of papers studied injury severity of HRGC crashes and used this criterion to evaluate control devices and other related factors at HRGCs. It was also mentioned that there was a lack of research on hazmat release crashes reported at HRGCs. The question that may arise is whether the factors that increase/decrease crash severity at HRGCs are consistent with the factors that increase/decrease the probability of hazmat release (positive correlation between crash severity and hazmat release). This consistency may question the importance of this study. To investigate this possibility, Table 6.4 summarized the results of six studies regarding crash severity at HRGC, and the results of this study for comparison. It should be noted that, although some variables were defined differently in some studies, the final results were consistently reported in this table.

Table 6.4 Comparison of the Results of Six HRGC Crash Severity Studies with Hazmat Release

	Crash Severity						Hazmat Release	
Variables	(Hao and Daniel 2013)	((Haleem and Gan 2015)	(Eluru et al. 2012)	(Shanshan Zhao, Iranitalab, and Khattak 2016)	(Y. Kang and Khattak 2017)	(Shanshan Zhao and Khattak 2015)	Highway User	Train
TYPACC2	—	I	I	I	I	I	NS	NS
STANDARDFLS	—	—	NS	NS	I	—	D	NS
CROSSBUCKS	—	—	D	NS	I	—	D	NS
PUBLIC	—	—	—	—	—	—	I	NS
TYPRR2	—	—	—	—	—	—	D	I
TYPRR3	—	—	—	—	—	—	D	NS
FREIGHT	—	—	—	I	—	I	I	NA
OTHER	—	—	NS	—	—	—	D	NS
TYPVEH2	I	D	NS	NA	D	D	NS	I
TYPVEH3	I	D	D	NA	NS	—	NS	NS
TYPVEH4	NA	NS	—	NA	—	—	NA	NS
TYPVEH5	I	NS	—	NA	I	—	NA	I
TEMP	—	—	D	NS	—	—	NS	D
WEATHER2	I	NS	NS	NS	I	—	NS	NS
WEATHER3	I	NS	D	I	NS	—	NS	NS
WEATHER4	I	D	D	I	D	—	NS	I
DEVELTYPE2	D	NS	—	NS	NS	—	NS	NS
DEVELTYPE3	D	NS	—	I	NS	—	NS	NS
DEVELTYPE4	D	D	—	NS	D	—	NS	NS
DEVELTYPE5	D	NS	—	NS	NS	—	NS	NS
OFFPEAK	D	—	—	—	—	—	—	—
VEHSPD	I	—	—	NA	I	I	NS	NS
VISIBLTY1	I	—	—	—	NS	NS	NS	NS
VISIBLTY3	I	—	—	—	I	D	NS	NS
VISIBLTY4	I	—	—	—	I	NS	NS	NS
TRNSPD	I	I	I	I	I	I	NS	NS
DRIVAGE	I	I	I	I	I	I	NS	NS
NONPAVED	I	—	—	—	—	—	—	—
AADT	I	D	—	NS	D	—	—	—
DRIVGEN	—	I	I	I	I	I	NS	NS
BELLS	—	D	—	I	—	—	NS	NS
GATES	—	—	I	NS	NS	—	NS	NS
HWYTRFICSIG	—	—	NS	—	NS	—	NS	NS
AUDIBLE	—	—	NS	—	NS	—	NS	NS
STOPSIGNS	—	—	I	—	D	—	NS	NS
NBRCARS	—	—	—	—	I	—	NS	NS

—: Not Considered in Study, NS: Not Significant, NA: Not Applicable, D: Decrease, I: Increase

This comparison shows that there were variables that affected crash severity in different studies, almost consistently, but were not associated with hazmat release probability, such as type of crash, train speed, driver age and gender, vehicle speed and some types of land-use. The effects of types of highway user, temperature and weather on crash severity were inconsistent throughout the severity papers. While these variables were not significant in hazmat release from trucks, some of them affected hazmat release from trains, but not necessarily in the same way (direction) as in the crash severity. The positive effects of standard flashing-light signals, railroad crossbucks and other control devices on hazmat release from trucks were not observed in the majority of the crash severity literature. Public/private HRGCs and type of railroad were not considered in the reviewed crash severity studies, while they were associated with hazmat release. Freight trains increased crash severity and the probability of hazmat release from trucks in crashes at HRGCs. In general, with an exception of some cases, crash severity modeling results were not consistent with hazmat release modeling outcomes, indicating that policies and countermeasures based on crash severity studies may not be relevant to decreasing hazmat release in crashes at HRGCs. Thus, this underscores the necessity of investigating hazmat release in crashes at HRGCs.

Large proportion of missing values in potentially important variables in the dataset and consequently, not using those variables in the model specifications was a limitation in this research. These variables included details about HRGC control devices, actions of highway users during crashes, sight obstructions, type of hazmat, roadway conditions, etc. Similar to chapters 4 and 5, this unobserved heterogeneity and its likely effects on the parameter estimates, conclusions and recommendations of this chapter should be considered in using the models in practice. Examples of these possible effects include the counterintuitive results regarding the impacts of public/private HRGCs, or HRGCs with crossbucks on hazmat release in this chapter.

For future studies, researchers may address the data issue by using datasets with fewer missing values/variables. Other modeling methods can be utilized for analyzing hazmat-related crashes at HRGCs that might lead to further insights. Short-term and long-term costs and damages of hazmat release at HRGCs may be studied to prioritize countermeasures and policies regarding public safety improvements at HRGCs.

CHAPTER 7 PREDICTION OF HAZARDOUS MATERIALS RELEASE IN TRAIN INCIDENTS AND CARGO TANK TRUCK CRASHES

7.1 Introduction

Quantifying conditional probability of release of hazmat from trains in rail incidents and CTTs in highway crashes assists safety agencies and shippers in decision-making, as this probability is an important component of hazmat transportation risk (other components include probability of occurrence of an incident, and consequences of hazmat release).

The objective of this chapter was providing computational tools with reliable performance for quantifying probability of hazmat release in train incidents and CTT crashes. Hazmat release was considered as a binary response variable (release or no release), and statistical and machine learning classification methods were utilized to probabilistically classify this binary outcome using explanatory variables. The explanatory variables included incident/crash, railroad/roadway, environment, and train/CTT characteristics. Some of the incident/crash characteristics were also outcomes of the incident/crash, and separate tools were developed for their estimation to use in the hazmat release models. The datasets were Federal Railroad Administration (FRA) 2012-March 2018 rail equipment incident data, and combined Nebraska and Kansas 2010-2017 police reported traffic crash data. Classification methods comprised of logistic regression, naïve Bayes, random forests (RF), and support vector machines (SVM). The performance assessment of the various methods utilized different criteria, leading to usage recommendations for different purposes.

7.2 Additional Literature Review

The additional literature review covers the use of methods of this chapter in the transportation safety literature.

Injury severity of crashes is a multiclass categorical variable and statistical models and machine learning techniques are intensively used for classification and inference in this field. Examples of statistical models for analyzing injury severity are logistic regression or multinomial regression (Abdel-Aty and Keller 2005; Abdel-Aty and Abdelwahab 2004; Shaheed and Gkritza 2014; Shanshan Zhao and Khattak 2015; S. Zhao, Iranitalab, and Khattak 2018), while examples of machine learning include SVM, RF, and neural networks (Iranitalab and Khattak 2017; Li et al. 2012; Abdelwahab and Abdel-Aty 2001). This review did not uncover the use of the majority of the methods employed in this study for classification and probability estimation of hazmat release from trains and CTTs.

7.3 Methods

In risk analysis of hazmat transportation, the ability to accurately estimate the probability of hazmat release in rail incidents or CTT crashes is important. As was discussed in section 1.3, in the context of hazmat transportation, risk has different definitions. The majority of them include a form of a multiplication of the probability of release from a hazmat carrier by a measure of consequences of release. Probability of release is comprised of probability of occurrence of an incident/crash for a hazmat carrier and the conditional probability of release given the incident/crash. Some studies have investigated probability of occurrence of incidents/crashes for hazmat-carrying trains and trucks, e.g. (Anderson and Barkan 2004; Harwood, Viner, and Russell 1990). This chapter focused on estimating probability of hazmat release given an incident/crash using classification methods for trains and CTTs. The binary variable hazmat release given an incident/crash (yes/no) was the response variable and the explanatory variables included incident, railroad, environment, and train characteristics in train incidents and crash, trucks, roadway, environment, and driver characteristics for the CTT crashes.

Similar to chapter 4, this chapter classified hazmat release for trains at two levels: train and car. In the train-level classification each row of data was a hazmat-carrying train involved in an incident, while in the car-level classification each row was a hazmat-carrying car on a train involved in an incident. The predicted quantity in the train-level and car-level approaches were probability of release from trains and cars, respectively. The explanatory variables at each level changed accordingly as in chapter 4. The number of cars derailed/damaged in each incident was used in calculation of some of the train-level explanatory variables. Since this variable was also an outcome of the train incidents, predicting its values was necessary to use in the hazmat release classification. Therefore, tools for this prediction were also developed in this study and number of derailed/damaged cars was the count response variable.

Classification of hazmat release for CTTs was a similar procedure. Each row of data was a hazmat-carrying CTT involved in a crash. One of the explanatory variables that was also an outcome of the crash was rollover; a binary variable that indicated if the CTT rolled over in the crash. A similar set of explanatory variables were used for classifying CTT crashes to rollover/no rollover for use in the hazmat release classification. In the rollover classification, data comprised of the CTT crashes regardless of what the CTT has been carrying, hazmat or non-hazmat (since the probability of rollover was under study).

In summary, this study involved four classifications and estimation of a count regression model. The classifications include train-level and car-level classification of hazmat release, rollover and hazmat release classification of CTTs, and the count regression pertained to the number of derailed/damaged cars per train incident. The classifiers and the regressors were developed based on a training dataset and compared using a test dataset. The classification and regression methods and the performance evaluation tools were introduced in chapter 3.

7.4 Datasets

Rail incidents and CTT crashes were the two datasets used in this study. This section introduces the datasets, along with their variables and statistics.

7.4.1 Rail Dataset

Railroad reported incidents including derailments, collisions, crossing incidents and other incidents involving a hazmat-carrying train were extracted from the January 2012-March 2018 U.S. rail equipment incident database (Federal Railroad Adminsitration Office of Safety Analysis 2017), with 2012-2016 subset as the training dataset and January 2017-March 2018 as the test dataset. The training dataset consisted of 2581 incidents, 2787 trains, and 39162 hazmat cars and the test dataset had 579 incidents, 615 trains and 8318 hazmat cars. Car-level data was generated based on the original train-level data using information on number of hazmat-carrying cars, and number of cars that released hazmat. Weight of hazmat cars were approximated by dividing the gross weight of trains (excluding the power units) by the number of cars in each train. Table 7.1 and Table 7.2 present the variables and their statistics of the train-level and car-level data, respectively. Similar to chapter 4, track classes 1 and X were aggregated in one level for the track class variable, as they represented the same maximum speed for freight trains (10 mph). Track classes 5 to 9 were aggregated into one level as they were infrequent in the data.

Table 7.1 Descriptive Statistics for the Train-Level Incident Data

Variable	Values and Statistics (training dataset %, test dataset %)
Response Variables	
Hazmat Release	0 = No (96.73%, 97.07%), 1 = Yes (3.26%, 2.93%)
Number of Derailed/Damaged Cars	Training: Mean = 1.27, SD = 1.66, Test: 1.21, SD = 1.61
Explanatory Variables	
Incident Characteristics	
Type of incident	1 = Derailment (62.68%, 62.76%), 2 = Collision (12.77%, 9.11%), 3 = Crossing (8.50%, 9.43%), 4 = Others (16.04%, 18.70%)
Proportion of damaged/derailed hazmat cars to all hazmat cars	Training: Mean = 0.2504, SD = 0.3924, Test: Mean = 0.2550, SD = 0.3928
Locomotive(s) derailed	0 = No (91.96%, 93.66%), 1 = Yes (8.04%, 6.34%)
Proportion of damaged/derailed cars to all cars	Training: Mean = 0.0989, SD = 0.1820, Test: Mean = 0.1079, SD = 0.1987
Cause of incident	E = Mechanical and Electrical Failures (12.16%, 13.50%), H = Human Factors (39.25%, 38.37%), M = Miscellaneous (20.99%, 20.33%), S= Signal and Communication (3.01%, 3.90%), T= Track, Roadbed and Structures (24.58%, 23.90%)
Railroad Characteristics	
Type of railroad (Interstate Commerce Commission)	1 = Class I (83.05%, 85.04%), 2 = Class II (0.90%, 0.33%), 3 = Class III (16.05%, 14.63%)
Method of operation	1 = Signal indication (24.26%, 28.94%), 2 = Direct train control (6.71%, 6.99%), 3 = Yard/restricted limits (2.08%, 2.44%), 4 = Block register territory (0.47%, 0.00%), 5 = Other than main track rules (66.49%, 61.63%)

Track class	1 = Classes 1 and X (67.60%, 61.95%), 2 = Class 2 (7.61%, 8.29%), 3 = Class 3 (6.71%, 7.80%), 4 = Class 4 (14.46%, 17.40%), 5 = Classes 5 to 9 (3.62%, 4.55%)
Type of track	1 = Main (32.44%, 37.40%), 2 = Yard (59.78%, 53.01%), 3 = Siding (2.37%, 2.60%), 4 = Industry (5.42%, 6.99%)
Environmental Characteristics	
Temperature	Training: Mean = 58.62, SD = 22.28, Test: Mean = 56.58, SD = 23.10
Visibility	1 = Dawn (7.86%, 7.48%), 2 = Day (42.59%, 41.95%), 3 = Dusk (7.39%, 8.13%), 4 = Dark (42.16%, 42.44%)
Weather	1 = Clear (66.49%, 65.37%), 2 = Cloudy (22.53%, 25.53%), 3 = Rain (7.14%, 6.83%), 4 = Fog (1.15%, 0.98%), 5 = Sleet (0.25%, 0.33%), 6 = Snow (2.44%, 0.98%)
Train Characteristics	
Train speed (mph)	Training: Mean = 12.37, SD = 14.54, Test: Mean = 12.88, SD = 15.26
Train gross tonnage (ton)	Training: Mean = 4404, SD = 4667.70, Test: Mean = 5111.04, SD = 4742.96
Proportion of hazmat tank-cars to all tank-cars	Training: Mean = 0.2947, SD = 0.3095, Test: Mean = 0.2761, SD = 0.3038
Remote control locomotive	0 = No (80.19%, 85.04%), 1 = Yes (19.81%, 14.96%)

(Note: Data obtained from the FRA safety database (Federal Railroad Adminsitration Office of Safety Analysis 2017))

Table 7.2 Descriptive Statistics for the Train Car-Level Incident Data

Variable	Values and Statistics (training dataset %, test dataset %)
Response Variable	
Hazmat Release	0 = No (99.38%, 99.46%), 1 = Yes (0.62%, 0.54%)
Explanatory Variables	
Incident Characteristics	
Type of Incident	1 = Derailment (67.46%, 65.66%), 2 = Collision (11.89%, 9.59%), 3 = Crossing (10.14%, 9.37%), 4 = Others (10.51%, 15.38%)
Locomotive(s) derailed	0 = No (89.93%, 90.53%), 1 = Yes (10.07%, 9.47%)
Cause of incident	E = Mechanical and Electrical Failures (14.38%, 17.25%), H = Human Factors (35.03%, 34.70%), M = Miscellaneous (20.01%, 21.78%), S= Signal and Communication (1.65%, 1.60%), T= Track, Roadbed and Structures (28.93%, 24.67%)
Railroad Characteristics	
Method of operation	1 = Signal indication (32.67%, 40.19%), 2 = Direct train control (8.25%, 9.99%), 3 = Yard/restricted limits (2.75%, 2.55%), 4 = Block register territory (0.60%, 0.00%), 5 = Other than main track rules (55.72%, 47.27%)
Track class	1 = Classes 1 and X (57.83%, 48.86%), 2 = Class 2 (9.75%, 9.44%), 3 = Class 3 (10.03%, 13.18%), 4 = Class 4 (20.18%, 23.61%), 5 = Classes 5 to 9 (2.21%, 4.92%)

Type of track	1 = Main (43.11%, 51.02%), 2 = Yard (48.92%, 39.87%), 3 = Siding (2.80%, 3.77%), 4 = Industry (5.17%, 5.34%)
Environmental Characteristics	
Temperature	Training: Mean = 57.30, SD = 22.57, Test: Mean = 54.01, SD = 24.49
Visibility	1 = Dawn (8.15%, 65.69%), 2 = Day (43.68%, 22.93%), 3 = Dusk (6.81%, 9.91%), 4 = Dark (41.37%, 42.25%)
Weather	1 = Clear (65.81%, 63.69%), 2 = Cloudy (22.60%, 22.93%), 3 = Rain (6.84%, 9.91%), 4 = Fog (2.06%, 0.72%), 5 = Sleet (0.25%, 0.04%), 6 = Snow (2.45%, 2.72%)
Train/Car Characteristics	
Train speed (mph)	Training: Mean = 13.89, SD = 14.61, Test: Mean = 14.47, SD = 15.06
Tank car tonnage (ton)	Training: Mean = 77.30, SD = 73.19, Test: Mean = 80.75, SD = 43.29
Remote control locomotive	0 = No (88.37%, 91.67%), 1 = Yes (11.63%, 8.33%)

(Note: Data obtained from the FRA safety database (Federal Railroad Adminsitration Office of Safety Analysis 2017))

7.4.2 CTT Dataset

For the CTT classification, 2010-2017 police-reported crash data from the states of Nebraska and Kansas were combined (obtained from Nebraska and Kansas Departments of Transportation), with 2010-2016 as the training dataset and 2017 as the test dataset. Crashes with the involvement of CTTs were extracted from the combined dataset. This resulted in 2015 crashes with a CTT involved and 546 crashes with a hazmat-carrying CTT involved in the training data. These numbers were 183 and 32 in the test data. Trainings for truck rollover used all the CTT-involved crashes (carrying hazmat or not), while training for hazmat release used a subset of the data with hazmat-carrying trucks only. The variables and their statistics are presented in Table 7.3 for all CTT crashes and Table 7.4 for hazmat-carrying CTT crashes.

Table 7.3 Descriptive Statistics for the CTT Crash Data

Variable	Values and Statistics (training dataset %, test dataset %)
Response Variable	
Rollover	1 = No (84.57%, 93.44%), 2 = Yes (15.43%, 6.56%)

Explanatory Variables	
Crash Characteristics	
Vehicle Point of Impact	1 = None (3.08%, 4.37%), 2 = Center front (17.07%, 17.49%), 3 = Center rear (6.75%, 7.10%), 4 = Left front (10.87%, 12.57%), 5 = Left rear (5.66%, 9.84%), 6 = Left side (11.76%, 8.74%), 7 = Right front (14.29%, 8.20%), 8 = Right rear (5.26%, 10.93%), 9 = Right side (13.00%, 12.57%), 10 = All areas (0.99%, 1.64%), 11 = Other (11.27%, 6.56%)
Type of Crash	1 = Collision (86.60%, 92.35%), 2 = Non-collision (13.40%, 7.65%)
Object Involved	1 = No (81.24%, 83.06%), 2 = Yes (18.76%, 16.94%)
Vehicle Movement	1 = Straight (61.04%, 59.02%), 2 = Turning left (8.24%, 9.29%), 3 = Turning right (7.44%, 6.01%), 4 = Changing lanes (2.73%, 4.92%), 5 = Slowing/stopped in traffic (7.49%, 9.29%), 6 = Backing (2.68%, 2.73%), 7 = Other (10.37%, 8.74%)
CTT Characteristics	
Vehicle Body Style	1 = Single-unit (20.89%, 14.75%), 2 = Tractor & semi-trailer (71.71%, 75.41%), 3 = Tractor with doubles/triples (0.84%, 1.63%), 4 = Truck tractor (0.30%, 2.19%), 5 = Truck with trailer (6.25%, 6.01%)
Vehicle Make	1 = Freightliner (22.63%, 25.14%), 2 = Internat. Harvester (10.87%, 8.20%), 3 = Kenworth (19.90%, 15.30%), 4 = Mack (5.16%, 1.64%), 5 = Peterbilt (14.39%, 28.42%), 6 = Other (27.05%, 21.31%)
Vehicle Age	Training: Mean = 7.55, SD = 6.62, Test: Mean = 7.59, SD = 7.49
Gross Vehicle Weight	1 = 10,000 lbs. or less (2.63%, 3.83%), 2 = 10,001 to 26,000 lbs. (9.33%, 19.13%), 3 = More than 26,000 lbs. (88.04%, 77.05%)
Roadway Characteristics	
Speed Limit	Training: Mean = 53.73, SD = 15.05, Test: Mean = 50.00, SD = 17.68
Number of Lanes	1 = One (4.27%, 3.28%), 2 = Two (61.89%, 55.74%), 3 = Three (3.57%, 6.56%), 4 = Four or more (30.27%, 34.43%)
Road Surface Type	1 = Asphalt (55.78%, 46.45%), 2 = Concrete (35.38%, 48.63%), 3 = Dirt (1.84%, 0.00%), 4 = Gravel (6.50%3.28%), 5 = Other (0.50%, 1.64%)
Road Surface Condition	1 = Dry (82.03%, 75.41%), 2 = Ice (3.03%, 8.20%), 3 = Sand/mud (0.99%, 0.00%), 4 = Slush (0.15%, 0.00%), 5 = Snow (3.42%, 3.82%), 6 = Wet (9.23%, 11.48%), 7 = Other (1.14%, 1.09%)
Road Level	1 = Level (77.52%, 85.24%), 2 = Hilltop (1.89%, 1.64%), 3 = Slope (20.60%, 13.12%)
Road Curvature	1 = Straight (89.53%, 88.52%), 2 = Curved (10.47%, 11.48%)
Intersection Involved	1 = No (59.85%, 52.46%), 2 = Yes (40.15%, 47.54%)
Railroad Involved	1 = No (98.96%, 98.91%), 2 = Yes (1.04%, 1.09%)
In Workzone	1 = No (95.43%, 93.44%), 2 = Yes (4.57%, 6.56%)
Driver Characteristics	
Driver's Sex	1 = Male (98.06%, 97.27%), 2 = Female (1.94%, 2.73%)
Driver's Age	Training: Mean = 47.55, SD = 12.94, Test: Mean = 47.81, SD = 13.17
Alcohol Related	1 = No (98.51%, 99.45%), 2 = Yes (1.49%, 0.55%)

Environmental Characteristics	
Weather Conditions	1 = Clear/Cloudy (86.15%, 85.25%), 2 = Blowing sand, soil, dirt, snow (1.34%, 2.73%), 3 = Fog, smog, smoke (1.49%, 1.09%), 4 = Rain/Sleet/… (0.10%, 8.74%), 5 = Severe crosswinds (6.80%, 0.00%), 6 = Snow (1.09%, 2.19%), 7 = Other (3.03%, 0.00%)
Light Conditions	1 = Daylight (73.50%, 78.14%), 2 = Dark (21.49%, 18.03%), 3 = Dawn/Dusk (5.01%, 3.83%)

(Note: Data obtained from Nebraska and Kansas Departments of Transportation)

Table 7.4 Descriptive Statistics for the Hazmat-Carrying CTT Crash Data

Variable	Values and Statistics (training dataset %, test dataset %)
Response Variable	
Hazmat Release	1 = No (87.00%, 87.50%), 2 = Yes (13.00%, 12.50%)
Explanatory Variables	
Crash Characteristics	
Vehicle Point of Impact	1 = None (3.48%, 3.13%), 2 = Center front (17.58%, 15.63%), 3 = Center rear (6.78%, 9.38%), 4 = Left front (10.07%, 9.38%), 5 = Left rear (5.68%, 12.5%), 6 = Left side (12.27%, 12.5%), 7 = Right front (13.37%, 9.38%), 8 = Right rear (4.03%, 9.38%), 9 = Right side (14.10%, 15.63%), 10 = All areas (0.37%, 0.00%), 11 = Other (12.27%, 3.13%)
Type of Crash	1 = Collision (86.08%, 90.63%), 2 = Non-collision (13.92%, 9.38%)
Object Involved	1 = No (85.35%, 90.63%), 2 = Yes (14.65%, 9.38%)
Vehicle Movement	1 = Straight (62.09%, 62.50%), 2 = Turning left (7.14%, 6.25%), 3 = Turning right (7.14%, 3.13%), 4 = Changing lanes (1.83%, 0.00%), 5 = Slowing/stopped in traffic (8.06%, 12.50%), 6 = Backing (1.47%, 3.13%), 7 = Other (12.27%, 12.50%)
Rollover	1 = No (84.57%, 90.63%), 2 = Yes (15.43%, 9.38%)
CTT Characteristics	
Vehicle Body Style	1 = Single-unit (21.25%, 15.63%), 2 = Tractor & semi-trailer (69.41%, 68.75%), 3 = Tractor with doubles/triples (1.47%, 0.00%), 4 = Truck tractor (0.37%, 9.38%), 5 = Truck with trailer (7.51%, 6.25%)
Vehicle Make	1 = Freightliner (22.63%, 28.13%), 2 = Internat. Harvester (11.36%, 6.25%), 3 = Kenworth (24.73%, 15.63%), 4 = Mack (4.21%, 0.00%), 5 = Peterbilt (28.21%, 37.50%), 6 = Other (11.17%, 12.50%)
Vehicle Age	Training: Mean = 6.30, SD = 5.30, Test: Mean = 5.44, SD = 6.12
Gross Vehicle Weight	1 = 10,000 lbs. or less (2.01%, 3.13%), 2 = 10,001 to 26,000 lbs. (5.13%, 6.25%), 3 = More than 26,000 lbs. (92.86%, 90.63%)
Roadway Characteristics	
Speed Limit	Training: Mean = 54.86, SD = 14.46, Test: Mean = 50.31, SD = 17.27

Number of Lanes	1 = One (3.85%, 6.25%), 2 = Two (60.26%, 46.88%), 3 = Three (3.85%, 12.50%), 4 = Four or more (32.05%, 46.88%)
Road Surface Type	1 = Asphalt (56.04%, 50.00%), 2 = Concrete (34.98%, 50.00%), 3 = Dirt (1.83%, 0.00%), 4 = Gravel (6.41%, 0.00%), 5 = Other (0.73%, 0.00%)
Road Surface Condition	1 = Dry (81.32%, 90.63%), 2 = Ice (4.40%, 3.13%), 3 = Sand/mud (1.28%, 0.00%), 4 = Slush (0.18%, 0.00%), 5 = Snow (4.40%, 0.00%), 6 = Wet (7.88%, 6.25%), 7 = Other (0.55%, 0.00%)
Road Level	1 = Level (76.37%, 84.38%), 2 = Hilltop (1.47%, 3.13%), 3 = Slope (22.16%, 12.50%)
Road Curvature	1 = Straight (89.19%, 96.88%), 2 = Curved (10.81%, 3.13%)
Intersection Involved	1 = No (63.19%, 50.00%), 2 = Yes (36.81%, 50.00%)
Railroad Involved	1 = No (98.53%, 93.75%), 2 = Yes (1.47%, 6.25%)
In Workzone	1 = No (95.97%, 100.00%), 2 = Yes (4.03%, 0.00%)
Driver Characteristics	
Driver's Sex	1 = Male (98.90%, 100.00%), 2 = Female (1.10%, 0.00%)
Driver's Age	Training: Mean = 48.76, SD = 11.92, Test: 47.94, SD = 10.68
Alcohol Related	1 = No (98.35%, 96.88%), 2 = Yes (1.65%, 3.13%)
Environmental Characteristics	
Weather Conditions	1 = Clear/Cloudy (86.81%, 90.63%), 2 = Blowing sand, soil, dirt, snow (1.10%, 0.00%), 3 = Fog, smog, smoke (0.73%, 0.00%), 4 = Rain/Sleet/… (6.59%, 9.38%), 5 = Severe crosswinds (0.92%, 0.00%), 6 = Snow (3.85%, 0.00%), 7 = Other (0.00%, 0.00%)
Light Conditions	1 = Daylight (72.89%, 68.75%), 2 = Dark (22.89%, 28.13%), 3 = Dawn/Dusk (4.21%, 3.125%)

(Note: Data obtained from Nebraska and Kansas Departments of Transportation)

7.5 Results

This section presents the results of the train (train-level and car-level) and CTT conditional hazmat release classification, along with CTT rollover classification and prediction of number of cars damaged or derailed in train incidents. While logistic regression, mixed logistic regression, naïve Bayes and Poisson regression do not have hyperparameters to tune, RF and SVM do require it. Also, since RF was trained using the under-sampling technique, cutoff probability was not adjusted (and the default 50% was used for classification). However, for other methods ROC curves were developed and new cutoff probabilities were adjusted. Table 7.5 and Table 7.6 present the adjusted cutoff probabilities, and the classification and prediction results for train and CTT, respectively. Figure 7.1 shows the ROC curves for all classification methods with adjusted cutoff probabilities.

The hyperparameters of RF (*v*, *t* and *n*) were tuned using grid search and out-of-bag cross validation. In other words, a range of values for these three hyperparameter were considered based on literature, and RFs were trained using all possible combinations of these values on the training set. Best out-of-bag performances (based on precision, recall, F_1 Score and AUC) resulted in the best trained RFs (in cross validation and final training, each RF was run 15 times and the average of the outcomes was used for comparison, due to randomness in the structure of RF). The values used in grid search were $v = 1,2, \dots, p$, $t = 10, 20, 50, 100, 200, 500, 1000$, and $n = 1, 10, 20, 50, 100$, where *p* is the number of explanatory variables. Similarly, SVM's hyperparameters (γ and *c*) were tuned using grid search and 5-fold cross validation. The grid search values included $\gamma = 2^{-15}, 2^{-13}, \dots, 2^{12}, 2^{14}$, and $c = 2^{-15}, 2^{-13}, \dots, 2^{12}, 2^{14}$. While different criteria yielded one single set of hyperparameters for SVM as the best performance in all cases, three different sets of hyperparameters were identified for RF in classification. So, three RFs are reported in Table 7.5 and Table 7.6.

The results showed the three RFs had the best performance in train-level hazmat release classification, based on different criteria. Two of RFs for car-level hazmat release classification had the best performance, as well, while the mixed logistic regression model had the best precision. According to RMSE, RF had the best prediction performance for number of cars damaged or derailed, while the Poisson regression had better TCE. In classification of CTT rollovers, naïve Bayes had the highest precision and F_1 score, one of the RFs had the best recall, and logistic regression had the highest AUC. SVM and one of the RFs had the highest precision and F_1 score for CTT hazmat release classification, while logistic regression and naïve Bayes performed better based on recall. Naïve Bayes had the highest AUC.

Table 7.5 Results of Train and Car-Level Hazmat Release Classification and Number of Damaged/Derailed Cars Prediction

Train-Level	**Method**	Logistic Regression		RF 1		RF 2		RF 3		Naïve Bayes		SVM	
	Parameters	-		$v = 16, t = 1000, n = 100$		$v = 2, t = 500, n = 1$		$v = 5, t = 1000, n = 10$		-		$\gamma = 2^{-15}$, $c = 2^{14}$	
	Cutoff	0.05		0.5		0.5		0.5		0.05		0.04	
	Release	0	1	0	1	0	1	0	1	0	1	0	1
	0	84.25%	15.75%	56.06%	43.94%	91.45%	8.55%	87.31%	12.69%	67.67%	32.33%	85.93%	14.07%
	1	50.00%	50.00%	0.00%	100.00%	41.11%	58.89%	35.56%	64.44%	38.89%	61.11%	38.89%	61.11%
	Precision	8.74%		6.42%		**17.19%**		13.28%		5.39%		11.58%	
	Recall	50.00%		**100.00%**		58.89%		64.44%		61.11%		61.11%	
	F_1 Score	14.88%		12.07%		**26.61%**		22.03%		9.91%		19.47%	
	AUC	71.73%		86.53%		84.20%		**87.45%**		72.59%		83.72%	
Car-Level	**Method**	Mixed Logistic Regression		RF 1		RF 2		RF 3		Naïve Bayes		SVM	
	Parameters	-		$v = 1, t = 500, n = 1$		$v = 3, t = 50, n = 1$		$v = 3, t = 1000, n = 1$		-		$\gamma = 2^{-2}$, $c = 2^{10}$	
	Cutoff	0.01		0.5		0.5		0.5		0.05		0.01	
	Release	0	1	0	1	0	1	0	1	0	1	0	1
	0	93.82%	6.18%	84.29%	15.71%	92.35%	7.65%	92.61%	7.39%	76.80%	23.20%	82.81%	17.19%
	1	42.22%	57.78%	21.15%	78.85%	32.44%	67.56%	31.11%	68.89%	24.44%	75.56%	37.78%	62.22%
	Precision	**4.84%**		2.65%		4.59%		4.83%		1.74%		1.93%	
	Recall	57.78%		**78.52%**		67.56%		68.89%		75.56%		62.22%	
	F_1 Score	8.93%		5.12%		8.59%		**9.02%**		3.40%		3.75%	
	AUC	80.30%		82.96%		**83.20%**		83.03%		80.53%		73.15%	

Number of Cars Damaged or Derailed	**Method**	Poisson Regression	RF	SVM
	Parameters	-	$v = 2, t = 1000, n = 1$	$\gamma = 2^{0}, c = 2^{14}$
	RMSE	2.6313	**2.4825**	2.9117
	TCE	**1.73%**	6.74%	9.47%

Table 7.6 Results of the CTT Hazmat Release and Rollover Classification

	Method	Logistic Regression		RF 1		RF 2		RF 3		Naïve Bayes		SVM	
	Parameters	-		$v = 21$ $t = 1000$ $n = 100$		$v = 3$ $t = 500$ $n = 1$		$v = 8$ $t = 1000$ $n = 10$		-		$\gamma = 2^{-8}$ $c = 2^{0}$	
Rollover	**Cutoff**	0.1		0.5		0.5		0.5		0.5		0.5	
	Rollover	0	1	0	1	0	1	0	1	0	1	0	1
	0	86.55%	13.45%	81.68%	18.32%	93.14%	6.86%	91.70%	8.30%	97.08%	2.92%	96.49%	3.51%
	1	16.67%	83.33%	8.33%	91.67%	32.04%	67.96%	23.33%	76.67%	33.33%	66.67%	33.33%	66.67%
	Precision	30.30%		25.98%		41.14%		39.32%		**61.54%**		57.14%	
	Recall	83.33%		**91.67%**		67.96%		76.67%		66.67%		66.67%	
	F_1 Score	44.44%		40.49%		51.25%		51.98%		**64.00%**		61.54%	
	AUC	**92.69%**		89.58%		89.98%		90.62%		88.79%		91.33%	
	Method	Logistic Regression		RF 1		RF 2		RF 3		Naïve Bayes		SVM	
	Parameters	-		$v = 23$ $t = 100$ $n = 50$		$v = 16$ $t = 500$ $n = 100$		$v = 4$ $t = 500$ $n = 10$		-		$\gamma = 2^{-2}$ $c = 2^{-4}$	
Hazmat Release	**Cutoff**	0.1		0.5		0.5		0.5		0.1		0.5	
	Release	0	1	0	1	0	1	0	1	0	1	0	1
	0	64.29%	35.71%	67.86%	32.14%	96.43%	3.57%	76.72%	23.28%	85.71%	14.29%	96.43%	3.57%
	1	25.00%	75.00%	28.33%	71.67%	50.00%	50.00%	50.00%	50.00%	25.00%	75.00%	50.00%	50.00%
	Precision	23.08%		24.16%		**66.67%**		23.44%		42.86%		**66.67%**	
	Recall	**75.00%**		71.67%		50.00%		50.00%		**75.00%**		50.00%	
	F_1 Score	35.29%		36.13%		**57.14%**		31.91%		54.55%		**57.14%**	
	AUC	62.50%		75.60%		69.88%		73.07%		**80.36%**		62.50%	

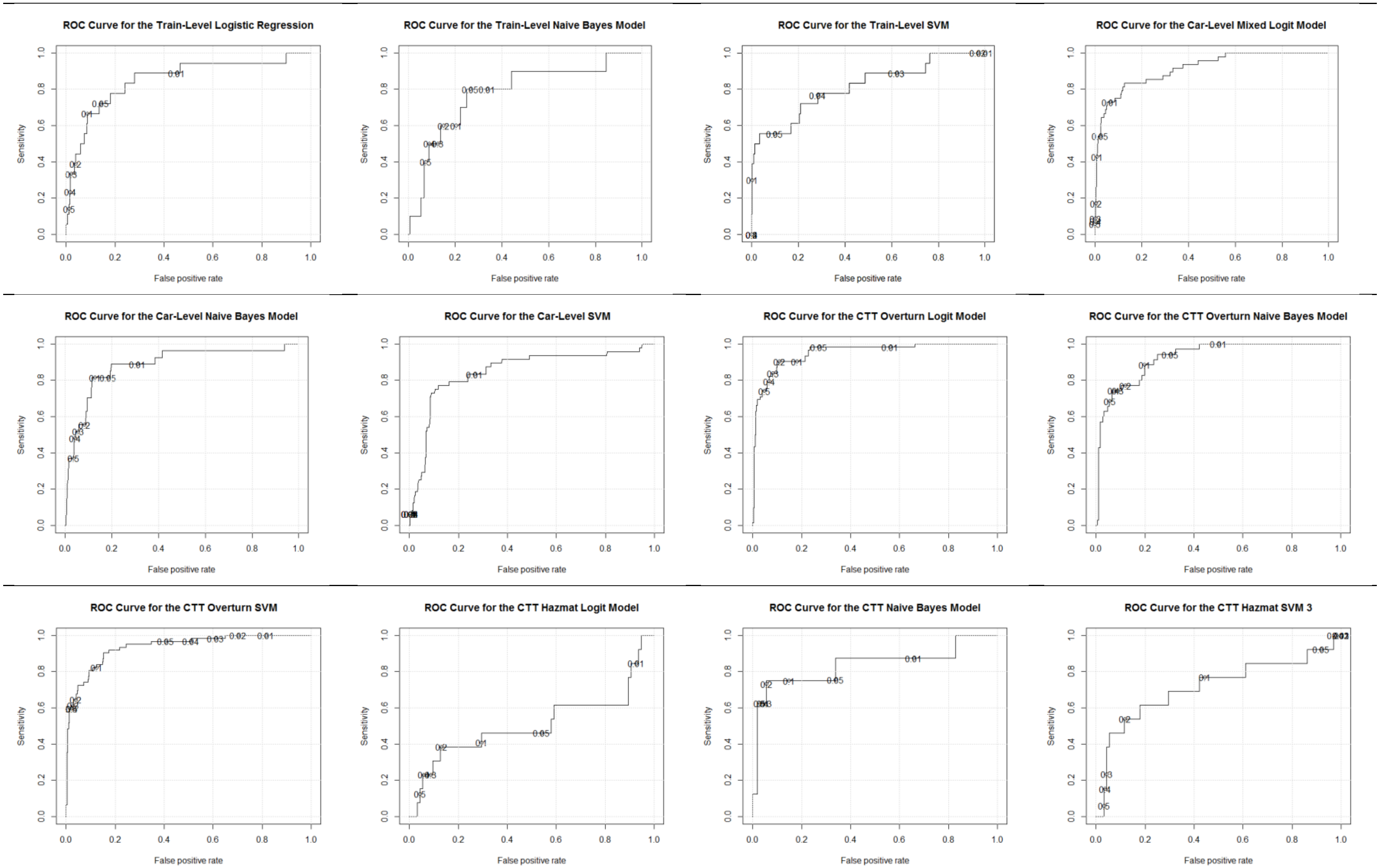


Figure 7.1 ROC curves for the classification methods with cutoff probability adjustment.

7.6 Discussion and Conclusions

The main use of estimating conditional probability of hazmat release from trains and CTTs is in risk assessment. Risk assessment combined with economic analyses may be used for cost-sensitive decision-making. The type of the decision-making problem affects the choice of the criteria for comparison of the methods, and consequently the choice of the classification method. In other words, the benefits and costs of correctly classifying a hazmat release or misclassifying non-release cases as release depends on the objectives of the analysis. In train-level classification, for example, based on all criteria, RF is preferred. Among different settings for RF, the choice of method depends on the usage. RF1 is preferred if the cost of misclassifying non-release cases as release is not high, and RF2 is preferred, otherwise. RF3 is the best choice if these costs are not easy to estimate or have too many fluctuations. Similar type of analysis for car-level and CTTs should be considered.

Selection of explanatory variables in this study was based on the reviewed literature, availability in the data, and avoidance of variables with missing values. In practice, variable selection may depend on other factors, as well. For example, a railroad company may have access to more detailed information about characteristics of the trains, cars, and operations. The use of these variables may affect the performance of the methods presented herein. Also, the purpose of classification and the stage of classification affects the availability of variables. Some explanatory variables may be outcomes of the incident/crash, and independent of all the other explanatory variables.

Such information may be unavailable and very hard to estimate, e.g. point of impact in a CTT crash.

The classification methods classify outcomes of the incidents/crashes based on the probabilities they calculate for each class. In case of hazmat risk assessment, it is important to estimate these probabilities accurately. However, many classifiers are unable to produce accurate probability estimates and their initial estimates need to be calibrated (Zhong and Kwok 2013; Niculescu-Mizil and Caruana 2005). Some of the most popular calibration methods are Platt scaling (Platt and others 1999) and isotonic regression (Zadrozny and Elkan 2001, 2002). Among the classification methods of this study, logistic regression's estimated probabilities are automatically calibrated, but RF, naïve Bayes and SVM need further calibration by the above methods, before using in risk assessment. Since RF used under-sampling, alternative calibration methods such as (Dal Pozzolo et al. 2015) can be utilized.

The major limitations of this chapter were related to the datasets. The FRA rail incidents dataset does not include car characteristics. Availability of such information may improve the classification performance of the car-level classification. The CTT crash data was limited only to two Midwestern states, which may make the results less comprehensive and generalizable (a national police-reported crash data is not available). Also, there were some missing variables in the CTT data that could potentially affect probabilities of rollover and hazmat release, e.g. detailed driver and CTT characteristics, crash speed, type and amount of loaded hazmat, etc. For future studies, using other incident/crash dataset may address such limitation. Other classifiers and regressors may be applied to the hazmat release problem and the results can compare to this study. Classification methods of this study can be implemented to the other components of hazmat risk, such as incident/crash frequency and release consequences in the future studies.

CHAPTER 8 MODELING OF FREQUENCY AND AGGREGATE MEASURES OF SEVERITY OF U.S. RAIL-BASED CRUDE OIL RELEASE INCIDENTS

8.1 Introduction

Production of crude oil has significantly increased in the U.S. over the past decade and trains transport a large portion of this crude oil to the refineries (26% in 2016 and 12% in 2016). Between 2008 and 2014, the number of annual train carloads of crude oil increased by about 5100%. Despite a modest reduction in crude oil carloads after 2015 due to changes in the U.S. pipeline capacity and international crude oil market, more than 200,000 carloads of crude oil were moved by rail in 2016 (Association of American Railroads 2017). This constitutes approximately one-fifth of the total hazmat moved by trains in that year in the U.S. (Bing et al. 2015). The transportation of large quantities of crude oil by trains potentially exposes people living near railways and the proximate environment to the ill effects of hazmat in cases of release incidents. The objective of this chapter is to estimate statistical models that can identify and quantify the effects of volumes and distances of rail-based crude oil transport and other macroscopic-level variables on the frequency and severity of crude oil release incidents. These models may enable decision- and policy-makers to work towards better preparation for dealing with such incidents, decreasing crude oil release costs, and predict these costs for future.

In this chapter, four OD-based statistical models were estimated for rail-based crude oil release incidents in the U.S.: one model for frequency and three models for measures of aggregate severity (number of released tank cars, quantity released, and total costs). State-to-state volume of crude oil movement (as a measure of exposure), transport distance, availability of other modes of transportation and number of competing class I railroad companies served as explanatory variables in the models. This chapter utilized the 2007-2016 Pipeline and Hazardous Material Safety Administration (PHMSA) rail-based crude oil release data. Since the state-to-state volume of crude oil movement is not available, a Linear Program (LP) was formulated to approximate these volumes of crude oil movement based on Energy Information Administration (EIA) higher-level production-consumption data (EIA divides the U.S. into 5 districts and reports the crude oil movement among these 5 districts). The estimated models quantified the effects of explanatory variables on frequency and aggregate measures of severity of crude oil release, along with providing a tool for predicting these safety measures for future.

The remainder of the chapter is organized as follows: section 2 provides an additional literature review, section 3 introduces the methods used in this chapter, section 4 presents all the datasets that were combined and used in the modeling, section 5 reports the modeling results, and conclusions and discussion in section 5 complete this chapter.

8.2 Additional Literature Review

The additional reviewed literature focused on transportation of crude oil, and macroscopic-level analysis of traffic crashes.

8.2.1 Crude Oil Transportation

Exclusive studies on surface transportation of crude oil received more attention in the early 2010’s following the crude oil boom in the U.S. Oke et al. presented a medium-term market equilibrium model of the North American crude oil sector to evaluate different strategies, such as restricting rail loads, increasing pipeline capacity, and lifting

U.S. crude oil export ban, for mitigating the environmental and public-safety risk due to crude oil transportation by rail (Oke et al. 2016). Liu proposed a method for risk management of crude oil rail transportation that accounted for track segment specific characteristics, train-specific characteristics, and population density along each segment (Liu 2016). Liu and Dick estimated unit-train crude oil transportation risk by frequency of location-specific rail defect inspection through an optimization framework (Liu and Dick 2016). Yazdi and Bagheri compared the risk of transportation of crude oil by pipelines, trains and trucks, through a case study and found pipelines as the safest mode (Yazdi and Bagheri 2017). Other studies focused on chemical characteristics of different types of crude oil, regarding their effects on transportation risk (David Lord et al. 2015; Andrews 2014).

8.2.2 Macroscopic-Level Accident Analysis

A common macroscopic-level accident analysis in the transportation safety literature is crash frequency modeling (Mannering and Bhat 2014). These studies frame analytic approaches to identify factors that affect the number of crashes occurring in a geographical unit (e.g. a roadway segment, an intersection or a census tract) over a specified time period (Dominique Lord and Mannering 2010). The models use different explanatory variables, including land-use, demographic, employment, roadway, and environmental characteristics (Hadayeghi, Shalaby, and Persaud 2010, 2003; Park and Lord 2007). Modeling techniques utilized to account for different aspects of accident data included models such as Poisson regression, negative binomial regression, duration, multivariate, mixed effects, spatial/temporal correlation, and non-parametric (Mannering and Bhat 2014; Dominique Lord and Mannering 2010). Several studies focused on modeling truck accident frequency (Miaou et al. 1992; Harwood, Viner, and Russell 1990, 1993; Joshua and Garber 1990), and some investigated train accident frequency for different type of accidents, especially derailments (Anderson and Barkan 2004; Liu, Rapik Saat, and Barkan 2017).

8.2.3 Summary

The additional literature review revealed the relatively recent crude oil transportation literature focused on risk assessment, market equilibrium, mode choice, and chemical aspects of crude oil. Despite the availability of macroscopic-level studies of traffic accidents, this review did not find any studies focused on modeling hazmat incident frequency or other aggregate measures for hazmat-related incidents. As well, this review did not uncover the use of OD-based accident frequency models in published literature.

8.3 Methods

The explanatory variables in this chapter comprised of state-to-state volume of crude oil shipment (as a measure of exposure), distance of shipment, availability of other modes of transportation, and the number of class I railroads competing for market. This chapter used Mixed-effects Negative Binomial Regression (MNBR) for modeling frequency and number of tank cars that released crude oil, and Mixed-effects Ordered Logit Models (MOLM) for modeling categorized quantity of release and total costs (the reason for categorization of these continuous variables is mentioned in the data and variables section). As a state-level crude oil movement data was not available to use as an exposure measure in the models, an LP was formulated for approximating the volumes of state-to-state crude oil movement volumes.

The EIA reports the movement of crude oil in the U.S. based on Petroleum Administration for Defense Districts (PADDs), which are geographic aggregations of the 50 states and the District of Columbia into five districts. Figure 8.1 presents a map of these districts. Based on the available information regarding annual state production of crude oil, annual state capacity of petroleum refineries, state-to-state transportation distance, unit-price of crude oil transportation for different modes (rail, pipeline and water), and the PADD-to-PADD movement of crude oil by transportation mode information, an LP was formulated to approximate annual state-to-state volume of crude oil movement. In other words, the LP disaggregates the PADD-to-PADD crude oil movement data to the state-to-state level based on the above additional information.

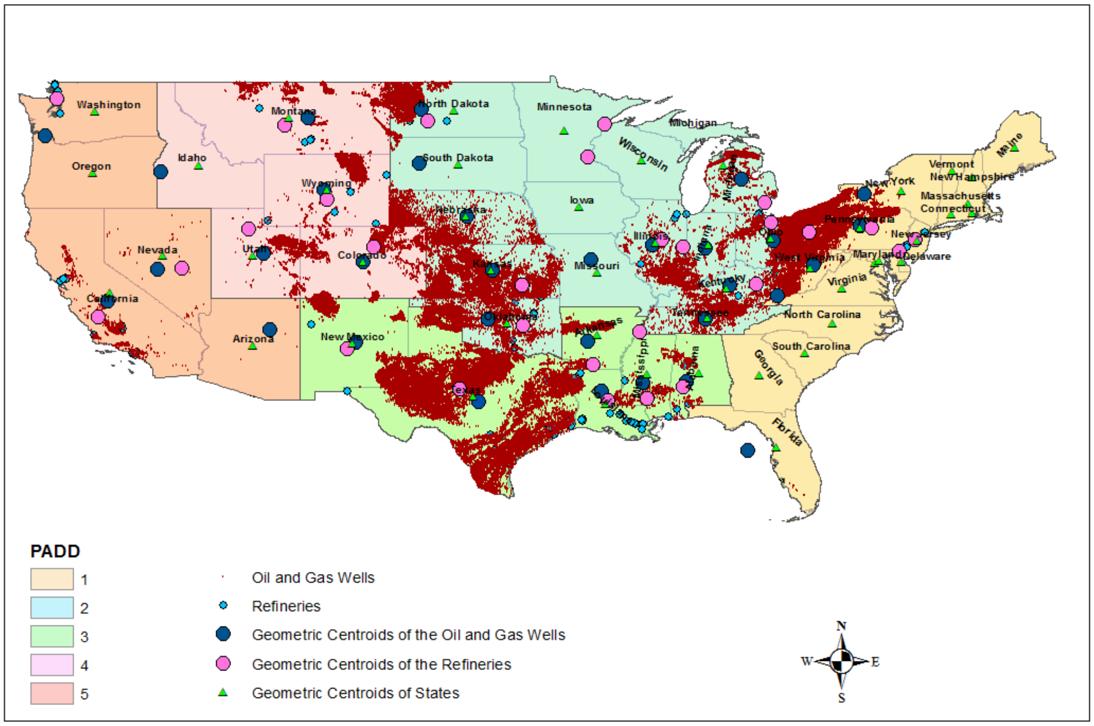


Figure 8.1 Map of U.S. states, PADDs, oil and gas wells, refineries, and their geometric centroids (from various sources mentioned in the data and variables section).

Let $x_{ij,m}$ be volume of crude oil movement from state *i* to refineries in state *j* by transportation mode *m* (rail, pipeline and water), d_{ij} be the defined distance from state *i* to state *j*, c_m be the cost per unit volume per unit distance of transportation of crude oil by mode *m*, P_i be the annual crude oil production of state *i*, R_j be the annual petroleum refinery capacity for state *j*, N_k be a set of states that belong to PADD *k*, and $T_{kl,m}$ be the annual volume of crude oil movement from PADD *k* to PADD *l* by transportation mode *m*. The formulated LP for minimizing the total cost of crude oil movement in the U.S., denoted by Z, is as follows:

$$Min\ Z = \sum_{i=1}^{50} \sum_{j=1}^{50} \sum_{m=1}^{3} x_{ij,m} d_{ij} c_m \tag{8.1}$$

subject to:

$$(i)\ \sum_{j=1}^{50}\sum_{m=1}^{3} x_{ij,m} = P_i \qquad \text{for } i = 1 \text{ to } 50$$

$$(ii)\ \sum_{i=1}^{50}\sum_{m=1}^{3} x_{ij,m} \leq R_j \qquad \text{for } j = 1 \text{ to } 50$$

$$(iii)\ \sum_{i\epsilon N_k}\sum_{j\epsilon N_l} x_{ij,m} = T_{kl,m} \qquad \text{for } k = 1 \text{ to } 5, l = 1 \text{ to } 5, m = 1\ to\ 3$$

$$(iv)\ x_{ij,m} \geq 0 \qquad \text{for } i, j = 1 \text{ to } 50 \text{ and } m = 1\ to\ 3$$

The objective function *Z* is the total costs of movement of crude oil among all the 50 U.S. states. Constraint *(i)* for each state i, assures that the volume of crude oil moved from state *i* to all other states *j* is equal to the total crude oil produced in state i. Constraint *(ii)* holds the annual volume of crude oil moved to each state less than or equal to the annual refining capacity of the state. Constraint *(iii)* satisfies the PADD-to-PADD crude oil movement by transportation mode among states, and Constraint *(iv)* is the non-negativity constraint. For 50 origins, 50 destinations, 3 modes of transportation, and 5 PADDs, the LP included 7500 decision variables, 150 type *(i)* equality constraints, 150 type *(ii)* inequality constraints, 60 type *(iii)* equality constraints, and 7500 non-negativity constraints. The Simplex method (Dantzig, Orden, and Wolfe 1955) was used to solve the LP in this study.

The underlying assumptions of the LP include:

- Minimizing the overall transportation costs of the movement of crude oil provides an approximation of the crude oil shippers' decision on the volumes and destinations of shipment,
- $c_m s$ by mode are equal across the U.S., regardless of origins and destinations,
- Crude oil produced in a certain year is shipped to refineries in the same year,
- Transportation cost is the only factor affecting mode and destination choice.

<u>8.4 Data and Variables</u>

The data used in this study comprised of a number of datasets obtained from different sources. These included U.S. crude oil release rail incidents data, state production of crude oil, crude oil wells and refineries locations, state capacity of crude oil refining, PADD-to-PADD data of crude oil movement by water, pipeline and rail, U.S. class I railroads maps, and U.S. crude oil pipeline and waterway maps. This section presents these datasets and the final variables.

Transportation distance was used as a cost factor in the LP (equation 8.1), and also used as an explanatory variable that affected frequency and severity of incidents. This study defined this distance as the geodesic (the shortest path between two points on a sphere) distance between each state’s origin points to all the states’ destinations points. Origin points of each state were defined as the geometric centroid of the crude oil wells in that state, and the destination points of each state was defined as the geometric centroid of the refineries located in that state. Origin/destination was the geometric centroid of the state, if there were not wells/refineries located in that state. The location information of 2016 U.S. oil and gas wells and 2017 U.S. refineries were obtained from FracTracker (FracTracker n.d.) and the EIA (Energy Information Administration (EIA) 2017a), respectively. This study calculated the geometric centroids of oil and gas wells and refineries in each state (origins and destinations), and the distances from all origins to all destinations using the geographic information system software *ArcGIS* version 10.5.1. Figure 8.1 presents this information.

The LP introduced in the methodology section was solved for ten years (2007-2016) to approximate the state-to-state crude oil movement volumes. The LP's input data was from different sources. Distance (d_{ij}) was defined as above and was assumed constant throughout the ten years. It was sufficient to consider the cost of moving crude oil by mode m, c_m, in a relative manner. Based on an internet search of crude oil carriers, the costs of moving crude oil by rail was assumed 7.15 times as large as pipeline and 5 times as large as water (c_{rail}= 5.0, c_{pipe}= 0.7 and $c_{water} = 1.0$). Despite the existence of spatial and temporal variations in these ratios, they were assumed constant in this study, as the LP was very insensitive to changes of these values (less than 1% changes in the output) due to consideration of constraint *(iii)* which assures the correct share of modes. Annual crude oil production (P_i), annual petroleum refinery capacity (R_j) and the annual PADD-to-PADD volume of crude oil movement were from EIA (Energy Information Administration (EIA) 2017b) for 2007-2016.

Two variables captured the possible effects of availability of other modes or other class I railroad companies on frequency and severity of incidents. This was based on the hypothesis that in case of availability of pipelines and/or waterway for movement of crude oil, the railroad companies may try to decrease their price to stay in a competitive mode by decreasing their costs, leading to a lower level of safety. Also, the larger the number of competing class I railroad companies are available between the origin and destination, similar intention may result in cheaper but less safe transportation. A binary variable accounted for availability of other modes based on the petroleum pipelines and waterways for petroleum movement maps, obtained from EIA (Energy Information

Administration (EIA) 2017a). A continuous variable captured the number of available class I railroads between origins and destinations, based on the class I railroad maps available from Association of American Railroads (Association of American Railroads: Freight Rail Works n.d.).

Ten-year data (2007-2016) of crude oil release incidents from trains in the U.S. was extracted from the PHMSA incident database by the Incident Reports Database Search tool (Pipeline and Hazardous Materials Safety Administration and Office of Hazardous Materials Safety 2018). According to PHMSA, the reported incidents are either reported through telephone within 12 hours after occurrence for more severe incidents or through a written notice within 30 days for other incidents. The incidents that require telephonic notice include cases "*where: 1) as a direct result of a hazardous material a person is killed or injured requiring admittance to a hospital, the general public is evacuated for one hour or more, a major transportation artery or facility is closed or shut down for one hour or more, or the operational flight pattern or routine of an aircraft is altered; 2) fire, breakage, spillage, or suspected radioactive contamination occurs involving a radioactive material; 3) fire, breakage, spillage, or suspected contamination occurs involving an infectious substance other than a regulated medical waste; 4) a release of a marine pollutant occurs in a quantity exceeding 119 gallons for a liquid or 882 pounds for a solid; 5) a situation exists of such a nature that, in the judgment of the person in possession of the hazmat, it should be reported; or 5) during transportation by aircraft, a fire, violent rupture, explosion or dangerous evolution of heat occurs as a direct result of a battery or battery-powered device. Other incidents* *include: 1) an unintentional release of a hazmat during transportation including loading, unloading and temporary storage related to transportation; 2) a hazardous waste is released; 3) an undeclared shipment with no release is discovered; or 4) a specification cargo tank 1,000 gallons or greater containing any hazmat that received structural damage to the lading retention system or damage that requires repair to a system intended to protect the lading retention system, and did not have a release.*"

The extracted data included 460 release incidents, 680 released tank cars, 1,738,926 gallons of released crude oil and $65,608,355 total damages. Total damages included carrier/property damage, response/clean-up costs, evacuation costs, injuries/fatalities, and roadway closure (costs of evacuation were assumed $250 per person-day (Saat et al. 2014), monetary costs of not-hospitalized injury as the only type of injury/fatality that occurred in the dataset was assumed $62,500 per injury (Iranitalab and Khattak 2017), and roadway closure was assumed to cost $218,000 per day (Erkut, Tjandra, and Verter 2007; Mallela and Sadavisam 2011)). This dataset included the origin and destination of movement of each train that was involved in the release incidents. Using this information, the annual frequency of incidents, number of tank cars, quantity of crude oil released, and total costs for each pair of states (with at least one incident) were extracted. Pairs of states with larger-than-zero approximated crude oil movement volumes were added to the dataset with zero for frequency and severity of incidents. Volumes and other variables (distance, other modes and other class I railroad companies) were also added. The final dataset comprised of 318 rows; each row was a pair of states with positive volume of crude oil exchange in one of the years 2007-2016. Table 8.1 presents a summary of the variables.

Table 8.1 Variables and Descriptive Statistics of the Final Dataset

Variable	Variable Type	Values and Statistics
		Response Variables
Frequency	Count	Min = 0, Max = 17, Mean = 1.3648, Var. = 5.6772
Number of Tank Cars	Count	Min = 0, Max = 35, Mean = 2.0440, Var. = 19.6511
Quantity Released	Continuous (gallons)	Min = 0, Max = 475176.00, Mean = 5451.20, Var. = 1.93E+09
	Categorical	Categories: = 0, 0 < ≤100, 100 < ≤10000, >10000 Ratios: 0 (45.77%), 1 (47.34%), 2 (04.07%), 3 (02.82%)
Total Costs	Continuous (2016 U.S. Dollar)	Min = 0, Max = 25,632,806, Mean = 205,669, Var. = 2.71E+11
	Categorical	Categories: = 0, 0 < ≤15000, 15000 < ≤100000, >100000 Ratios: 0 (56.43%), 1 (33.86%), 2 (04.39%), 3 (05.33%)
		Explanatory Variables
Volume (*volume*)	Continuous (1000 barrels)	Min = 0, Max = 1.54E+05, Mean = 1.75E+04, Var. = 9.35E+08
Distance (*distance*)	Continuous (miles)	Min = 67.03, Max = 2384.39, Mean = 742.0607, Var. = 2.20E+05
Other Modes (*omodes*)	Dichotomous	Yes (38.99%), No (61.01%)
Number of Class I Railroad Companies (*railroads*)	Count	Min = 0, Max = 3, Mean = 1.3648, Var. = 0.8066

The variances of the two continuous response variables (quantity released and total costs) were very large. This was due to a few extremely large values relative to the other values in these two variables, which could cause biased estimates, if a linear regression model was utilized (Nachtsheim et al. 2004). Natural logarithm or a root transformation were possible solutions for this issue, however as logarithm of zero is not computable and model interpretation of a root transformed response variable is not as conclusive, an ordinal categorization of these variables was preferred. Categorization also alleviated the effects of possible inconsistency and inaccuracies in reporting and approximating costs and quantities. The thresholds of the categories were determined based on the variables' dispersion between maximum and minimum values, and abating the effects of the very large values without excluding them.

8.5 Modeling Results

This section presents the results of the four models estimated for frequency and aggregate measures of severity of crude oil release rail incidents. The frequency model used the number of incidents between each pair of states with positive crude oil transportation volume as the response variable in an MNBR. The three aggregate severity models used three criteria as response variables to account for severity of incidents, again, between each pair of states with positive crude oil transportation volume: 1) the number of tank cars that released crude oil; 2) the quantity of crude oil released; and 3) the total monetary costs of crude oil release. The tank car model was also a MNBR. The quantity of release and total costs models were MOLM.

In all the four models, the explanatory variables included volume and distance of crude oil shipment between pairs of states as continuous variables, availability of other modes of transportation as a binary variable (yes/no), number of available class I railroads as an integer variable (0-7), and quadratic and interaction terms for volume and distance variables. Three grouping factors were considered in the models: year; origin-destination state pairs; and origin-destination PADD pairs. All the four main variables (volume, distance, other modes and railroad companies) were used in the models regardless of their statistical significance, while the inclusion of quadratic and interaction terms, and the grouping factors were decided based on AICc values (Cavanaugh 1997).

Table 8.2 presents the estimated coefficients, likelihood ratio (LR) test p-values and estimated standard deviations of random effects for the intercepts. The quadratic form of volume of crude oil was significant in all models, while the quadratic form of distance and the interaction of distance and volume did not contribute to any of the models in terms of AICc, and were excluded. The contribution of three grouping factors varied among the models which led to different random effects specifications. Random effects for variables other than the intercept did not contribute to the models' AICc.

Equations 8.2 to 8.5 present the estimated equations for the frequency, tank cars, quantity, and costs models, respectively. In these equations $\hat{\mu}_i$ is the estimated frequency of crude oil rail incidents, $\hat{\mu}_t$ is the estimated number of tank cars released crude oil, $\hat{P}\left(Y_q \leq j\right)$ is the estimated probability of amount of crude oil release falling in a category equal or smaller than category j, $\hat{P}(Y_c \leq j)$ is the estimated probability of costs of crude oil release falling in a category equal or smaller than category j, X_1 is the amount of crude oil shipped between a pair of states in thousand barrels per year, X_2 is the geodesic distance between a pair of states in miles, X_3 is the availability of modes other than rail (pipeline/water) between a pair of states, X_4 is the number of available class I railroad companies between a pair of states, e is the base of natural logarithm and $N(\mu, \sigma^2)$ denotes a normal distribution with mean of μ and variance of σ^2. The other parameters are similar to their definitions in sections 3.3 and 3.4.

$$\hat{\mu}_i = e^{-2.76761+0.00003X_1-0.000000000168{X_1}^2+0.00131X_2+0.31678X_3+0.61329X_4+\hat{b}_s+\hat{b}_p}, \qquad (8.2)$$

$\hat{b}_s \sim N(0, 0.8090^2), \hat{b}_p \sim N(0, 0.2076^2).$

$$\hat{\mu}_t = e^{-2.79799+0.00004X_1-0.000000000207{X_1}^2+0.00148X_2+0.29936X_3+0.58017X_4+\hat{b}_s},$$
$$\hat{b}_s \sim N(0, 1.0840^2). \tag{8.3}$$

$$\frac{\hat{P}(Y_q \leq j)}{1-\hat{P}(Y_q \leq j)}$$
$$= e^{\hat{\beta}_{j0}-0.00009X_1+0.000000000462{X_1}^2-0.00508X_2-1.77976X_3-1.00642X_4+\hat{b}_s+\hat{b}_p+\hat{b}_y},$$
$$\hat{b}_s \sim N(0, 3.34268^2), \hat{b}_p \sim N(0, 1.88159^2), \hat{b}_y \sim N(0, 0.07415^2), \tag{8.4}$$
$$\hat{\beta}_{00} = 0, \hat{\beta}_{10} = 5.711, \hat{\beta}_{20} = 13.773, \hat{\beta}_{30} = 15.263.$$

$$\frac{\hat{P}(Y_c \leq j)}{1-\hat{P}(Y_c \leq j)}$$
$$= e^{\hat{\beta}_{j0}-0.00008X_1+0.000000000400{X_1}^2-0.00271X_2-1.18009X_3-0.55749X_4+\hat{b}_s+\hat{b}_p},$$
$$\hat{b}_s \sim N(0, 1.623^2), \hat{b}_p \sim N(0, 1.397^2), \tag{8.5}$$
$$\hat{\beta}_{00} = 0, \hat{\beta}_{10} = 4.433, \hat{\beta}_{20} = 8.206, \hat{\beta}_{30} = 9.068.$$

This chapter used percentage change (PC) and odds ratios (OR) for interpretation of MNBR and MOL, respectively. Confidence intervals (CI) were calculated for these two measures, along with point estimates to assist with model interpretation. As the quadratic form of the variable *volume* was in the final models, PC or OR for this variable was a function of itself, while they were independent for other variables. Therefore, Table 8.3 presents point estimates and 95% CIs for PCs and ORs for variables *distance*, *omodes*, and *railroads*, while Figure 8.2 illustrates these measures for *volume*, corresponding to a range of values for *volume*. Parametric bootstrap and Wald 95% CI's were calculated for MNBR and MOL models, respectively. The value of *c* in calculating PC and OR for *volume*, *distance*, *omodes*, and *railroads* were 1000, 100, 1, and 1, respectively.

Table 8.2 Estimation Results of the Four Incident Frequency and Severity Models

Model Components		Variables	Frequency Model			Tank Cars Model			Quantity Released Model			Total Costs Model		
			Coefficient	LR Test p-value		Coefficient	LR Test p-value		Coefficient	LR Test p-value		Coefficient	LR Test p-value	
Fixed Effects	Main Effect	Intercept	-2.76761			-2.79799			5.711, 13.773, 15.263			4.433, 8.206, 9.068		
		Volume	0.00003	0.00000	***	0.00004	0.00000	***	0.00009	0.00022	***	0.00008	0.00001	***
		Distance	0.00131	0.00000	***	0.00148	0.00000	***	0.00508	0.00000	***	0.00271	0.00005	***
		Other Modes	0.31678	0.14582		0.29936	0.23414		1.77020	0.06852	.	1.20350	0.07169	.
		Railroad	0.61329	0.00000	***	0.58017	0.00005	***	1.00220	0.09064	.	0.67910	0.13693	
	Quadratic and Interaction Terms	Volume²	-1.68E-10	0.00046	***	-2.07E-10	0.00015	***	-4.62E-10	0.01367	*	-4.00E-10	0.00129	***
		Distance²	—	—	—	—	—	—	—	—	—	—	—	—
		Volume*Dist.	—	—	—	—	—	—	—	—	—	—	—	—
Standard Deviation of Random Effects for the Intercept		States	0.809			1.084			3.34268			1.623		
		PADDs	0.2076			—			1.88159			1.397		
		Year	—			—			0.07415			—		

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

—: Not used in the model due to not contributing to the model according to AICc

Table 8.3 95% Confidence Intervals and Point Estimates of PCs and ORs

Variables	Frequency Model			Tank Cars Model			Quantity Released Model			Total Costs Model		
	Percentage Change			Percentage Change			Odds Ratios			Odds Ratios		
	Point Estimate	Lower Bound of CI	Upper Bound of CI	Point Estimate	Lower Bound of CI	Upper Bound of CI	Point Estimate	Lower Bound of CI	Upper Bound of CI	Point Estimate	Lower Bound of CI	Upper Bound of CI
Distance	14.01	7.78	19.08	15.92	8.00	21.10	1.66	1.31	2.11	1.31	1.14	1.51
Other Modes	37.27	-9.11	104.88	34.90	-18.24	117.16	5.93	0.84	42.05	3.25	0.85	12.43
Railroad	84.65	39.45	129.55	78.63	27.50	129.39	2.72	0.82	9.10	1.75	0.84	3.63

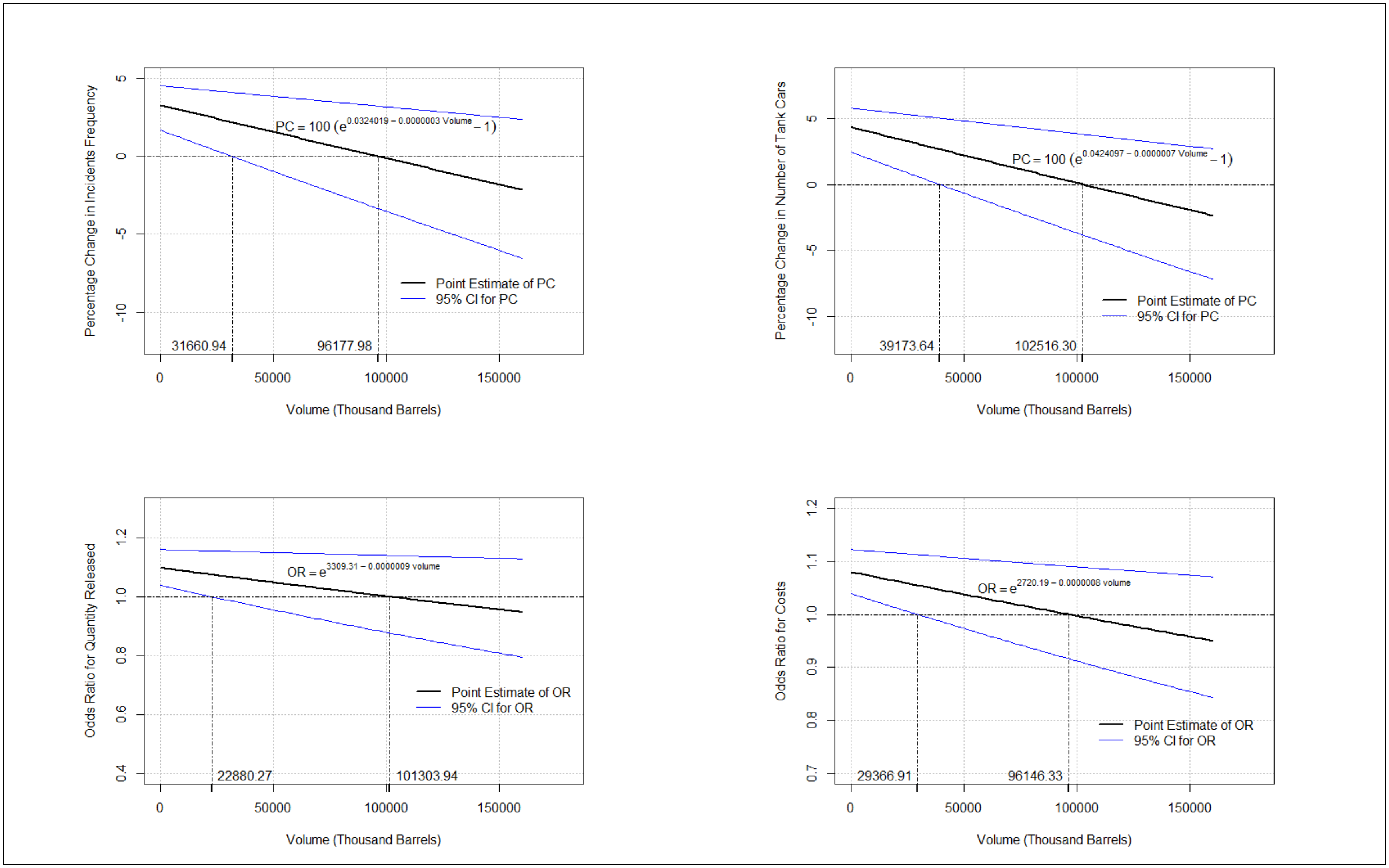


Figure 8.2 95% confidence intervals and point estimates of PC and OR for *volume* in the four estimated models.

Inclusion of value of “0” in CI’s calculated for PC’s and inclusion of value of “1” in CI’s calculated for OR’s denote the lack of evidence towards the statistical significance of the variable’s effects on or association with the response variable. With 95% confidence and holding all variables constant except the variable being interpreted, the models can be interpreted as follows:

For each 100-mile increase in the distance of crude oil shipment by rail between pairs of states, the frequency of crude oil release incidents increased by 7.78% to 19.08%. This change in distance led to 8.00% to 21.10% increase in the number of released tank cars. Corresponding to the 100-mile increase in distance, the odds of increase in quantity released from any of the predetermined levels to a higher level changed by 1.31 to 2.11 times. This change also resulted in 14% to 51% positive change in the odds of increase in total costs from any level to a higher level.

The models indicated lack of evidence for existence of any impacts from availability of modes of transportation (other than rail) from the origin states to the destination states on frequency or severity of crude oil release incidents. However, the number of class I railroad companies between states was statistically significant in the frequency and tank car models. One unit increase in the number of class I railroad companies resulted in an increase in the frequency of crude oil release incidents by 39.45% to 129.55% and in the number of release tank cars by 27.50% to 129.39%. Statistical evidence was not sufficient for the effects of this variable on quantity released or total costs.

Figure 8.2 shows how point estimates and CI's for *volume*'s PC and OR change as a function of *volume* itself. For each 1-million-barrel per year increase in the shipment of crude oil between a pair of states, sufficient statistical evidence was found regarding the response variables limited to restricted volumes. The frequency of incidents increased by variable amounts less than 5%, up to a volume point of approximately 32 million barrels. The number of tank cars released crude oil increased by a value between 0 to 6%, up to a volume point of approximately 40 million barrels. Quantity released and total costs increased by less than 20% and 15%, respectively and for up to approximately 23 million and 29 million barrels per year. The accurate amount of change can be calculated for all possible values of volume using the PC and OR estimated equations reported in Figure 8.2. With 95% confidence, sufficient statistical evidence was not found for effects of *volume* on the response variables for values higher than the ones mentioned. In all four models, approximately after 100 million barrels, increase in *volume* was identified to decrease frequency and aggregate severity of incidents, not statistically significantly. This may be due to lack of sufficient observation in this volume range, relative to lower values for volume.

8.6 Conclusions and Discussion

There are multiple factors that affect crude oil shippers' destination choice. These include type of crude oil, type and capacity of refineries in the destination, transportation monetary and non-monetary (e.g. time) costs, etc. Distance affects transportation costs as it is correlated with price of transportation and time. But due to presence of other variables mentioned above, farther refineries may be more attractive to crude oil shippers.

This chapter quantified the effects of distance on frequency and aggregate measures of severity of incidents. Therefore, shippers are suggested to include these values in terms of monetary or non-monetary costs in their destination choice procedure, potentially leading to closer destinations. Policy-makers may consider these quantified impacts, in terms of restricting shippers in their refinery destination choice and/or penalizing the choice of further destinations. This may decrease potential costs of crude oil release incident, benefiting the crude oil shippers and the society, simultaneously.

This chapter hypothesized that class I railroad companies attempt to decrease their costs (leading to more risky performance and more incidents), in order to stay competitive with other transportation modes (pipeline and water) and other class I railroad companies. Although presence of other modes was not found to exacerbate safety statistically, competition with other class I railroad companies was significantly associated with lower level of safety, in terms of frequency of incidents and number of tank cars released crude oil. Policy-makers may account for this factor in formulating safety policies. Also, based on this finding, incident response facilities may be more concentrated close to routes connecting origin-destination pairs with competing class I railroad companies for crude oil transportation.

As expected, the larger the volume of crude oil shipped from one state to another, the greater was the frequency and aggregate severity of incidents between the two states. The finding that the rate of increase in frequency and aggregate severity reduced by increase in volume can be attributed to several reasons: higher volumes of shipment of crude oil may be more frequent between those pairs of states that have this interaction routinely and consequently have a safer performance due to a lower level of uncertainty. Similarly, shipments with lower volumes may face more uncertainties due to smaller frequency, leading to more incidents and lower level of safety. Larger shipments of crude oil may occur more frequently between closer pairs of origin and destination, resulting in less sensitive-to-changes impacts on frequency and severity of incidents.

In this chapter, the four response variables, despite being interdependent, captured different phenomena with different objectives. While a safety planner may be more interested in prediction of the frequency and the costs of the incidents, emergency response or environmental agencies may find prediction of quantity of release more useful. Railroad insurance companies may prefer a prediction tool for costs of incidents, while number of released tank cars may be more important from a railroad engineering point of view. Policy-makers may focus on any of the models, based on their priorities. Frequency models consider all incidents equally, regardless of the size and consequences of release. Such an approach is advantageous as it considers potential costs in, for example, incidents with potentially large consequences that occurred with small consequences due to fast response or occurrence in a small-populated location. As a disadvantage, these models treat less-concerning incidents, such as non-accident releases, similar to very costly incidents. The use of the frequency model along with at least one of the aggregate severity models is recommended in practice.

The estimated models can be used for prediction in the future by inputting predicted values for the explanatory variables. Calculated distances among states may change in the future based on changes in number and locations of oil wells and refineries.

Transportation modes and railroad companies' information may be predicted for future to use in the models. The parameters of the LP, including productions, refining capacity, and PADD-to-PADD shipment volumes need projection for future, based on historic data. Variations of the LP may approximate volumes of transportation of other hazmat among states. The LP needs modification depending on the hazmat, available modes of transportation, type of origin/destination, available production and consumption data, and available auxiliary information (such as the PADD information in case of this chapter).

U.S. production of crude oil peaked in 2015 and faced a reduction in 2016. Also, the amount of crude oil moved by rail in the U.S. peaked in 2014 and decreased in 2015 and 2016. These along with safety improvements have led to a smaller number of rail crude oil-release incidents in 2015 and 2016, compared to 2014. However, this reduction does not affect the importance of this study because of several of reasons: the future of crude oil production and transportation depends on many factors, including international crude oil market and prices, domestic demand, economic factors, governmental decisions, etc., and the production and movement of crude oil may increase again in the coming years; similar sudden and unexpected increases in the rail transportation demand of crude oil or other hazmat may occur in the future, and this chapter provided a framework to study such occasions; and the amount of movement of crude oil by rail and the resulting release incidents, even after the recent reduction, is still considerable and necessary to address.

One limitation of this chapter was the inevitable assumptions made due to lack of data availability. The majority of these assumptions were made in the formulation and parameter tuning of the LP. It was attempted to minimize the sensitivity of the results due to the assumptions, however there may be still possible differences in the conclusions of this chapter as a result of different assumptions. The other limitation was in the categorization of the continuous response variables (quantity of crude oil release and total costs). It was preferable to model these two variables as continuous response variables and estimate the quantified effects of explanatory variables on them directly. Nevertheless, due to inconsistency in approximating and reporting of these values, very large variations, and the impossibility of the utilization of a useful transformation, these variables were categorized. Also, similar to chapters 4, 5 and 6, unobserved heterogeneity may be an issue in the models of this chapter as well and needs to be considered in using the models and their outcome in practice.

Future studies may focus on modeling frequency of crude oil-carrying train incidents, regardless of releasing the crude oil, and modeling the probability of release of crude oil, given an incident, separately. This approach can provide the effects of microscopic factors, such as characteristics of crude oil, train, railroad, etc., on occurrence of crude oil release incidents. Such a study requires a dataset of crude oil-carrying train incidents. The use of other statistical methods for modeling or machine learning methods for better prediction performance may also be investigated.

CHAPTER 9 JOINT AND SEPARATE MODELING OF TYPES AND CONSEQUENCES OF RAIL-BASED CRUDE OIL RELEASE INCIDENTS

9.1 Introduction

The transportation of large quantities of crude oil by rail potentially exposes people living in vicinity of railways and the proximate environment to the ill effects of hazmat in case of incidents leading to release. Various factors can affect the likelihood of incidents and consequences of crude oil release. Identifying these factors can assist crude oil shippers, railroad companies and policy-makers with decisions resulting in safer crude oil transportation.

The main objectives of this chapter were identification of the factors that affect the types and consequences of crude oil release from trains, quantification of these effects, and investigation of the effects of types and consequences of crude oil release on the resulting costs and damages. The considered factors that can impact types and consequences of release included characteristics of crude oil, tank cars, and release incidents. On January 2, 2014, PHMSA issued a safety alert warning that the type of crude oil transported from the Bakken region may be more flammable than traditional heavy crude oil (U.S. Department of Transportation (DOT), n.d.). A secondary objective of this chapter was testing the hypothesis of the PHMSA safety alert throughout the statistical modeling.

The investigation in this chapter involved estimation of two separate multinomial response models for types of crude oil release (gas dispersion, spillage and both) and consequences of crude oil release (fire, explosion and none), and one joint multinomial response model, for types and consequences of release. This chapter used the 2007-2016 PHMSA U.S. rail-based crude oil release data. Estimation of a robust linear regression model captured the effects of the types and consequences of crude oil release on total post-release costs, including carrier/property damage, response/clean-up costs, evacuation costs, injuries/fatalities, and roadway closure.

An additional literature review pertaining to shipping of crude oil follows this introduction. The ensuing section presents the methods of this chapter, dataset and variables. Results from the modeling effort, their interpretations, discussion and conclusions complete this chapter.

9.2 Additional Literature Review

Liu proposed a method for optimal safety risk management of rail transportation of crude oil. The model accounted for track segment specific characteristics (segment length, track class, method of operation, and annual traffic density), train-specific characteristics (train length, train speed, and tank car safety design), and population density along each segment. He measured segment-specific risk by the expected number of affected persons. Also, the model estimated the average interval between release incidents (Liu 2016). Oke et al. presented a medium-term market equilibrium model of the North American crude oil sector to evaluate different strategies for mitigating the environmental and public-safety risk due to crude oil transport by rail. They reported that an integrated policy of restricting rail loads, increasing pipeline capacity, and lifting US crude oil export ban can address medium-term risk of crude oil transport by rail (Oke et al. 2016).

Following PHMSA's safety alert regarding the possible extra flammability of the sweet light crude oil of the Bakken region relative to traditional heavy crude oil, several studies investigated the chemical characteristics of this crude oil. Lord et al. reviewed these studies and concluded that due to significant variability in criteria and procedures used in selection, acquisition, and analysis of crude oil samples, the available information was of insufficient quality to enable a meaningful comparison of crude oils. According to Lord et al., current methods for crude oil hazard classification and packing were often inadequate (David Lord et al. 2015). This provided the motivation to investigate the validity of PHMSA's safety alert in this research.

9.3 Methods

This section introduces the statistical approaches used in this chapter by first discussing multinomial response models (used for separate and joint modeling of types and consequences of release of crude oil), and then discussing continuous outcome models (used in modeling post-release costs).

9.3.1 Multinomial Response Models for Types and Consequences of Release

Two modeling approaches were considered: estimating two separate multinomial models for types and consequences of release; and estimating one joint model for types and consequences of release, assuming a joint probability distribution for these two variables. Figure 9.1 shows the outcomes of the release incidents based on their frequencies in the dataset.

In the separate approach, the response variables in the two estimated models were multinomial and indicated the type or consequence of crude oil release. One model with spillage (base level), gas dispersion, and simultaneous spillage and gas dispersion as categories of the response variable was estimated. The categories for the consequences model included fire, explosion and none (base level). Multinomial regression models were used with characteristics of crude oil, tank car, and release incidents as the explanatory variables.

In the joint approach, the response variable was constructed as a combination of the types and consequences of release. Based on the possible combined outcomes for the new response variable applicable to the dataset (refer to Figure 9.1), this variable had 5 levels: 1) spillage with no consequence; 2) spillage and fire; 3) spillage and explosion; 4) gas dispersion and no consequence; 5) both types of release and no consequence. Again, multinomial regression with a similar set of explanatory variables were used in the modeling.

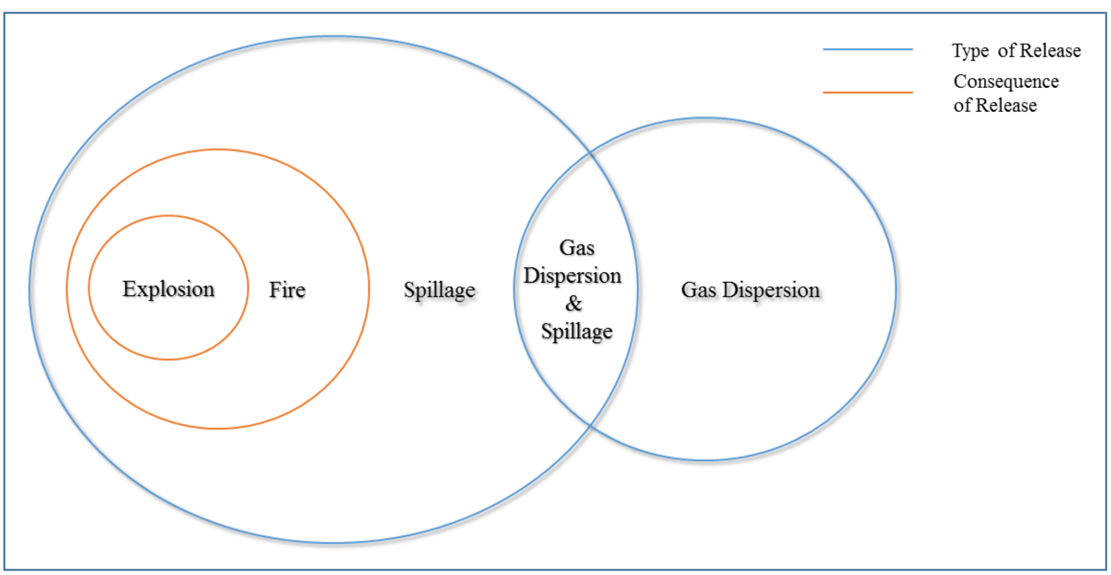


Figure 9.1 Types and consequences of crude oil release.

The definition of odds ratios in this chapter is slightly different from section 3.6. In the separate consequences model, for example, odds for explosion are the probability of explosion divided by the probability of no explosion in an incident of crude oil release. For *c*-unit increase in a continuous explanatory variable, *x*, the odds ratios are interpreted as "the odds of explosion vs. no consequences (the base level) change by *OR* times for every *c*-unit increase in *x*, holding the other variables constant". If *x* is a categorical explanatory variable, the value of *c* is 1, and the interpretation will be "the odds of explosion vs. no release consequence change by *OR* times as large for $x = 1$ than for $x = 0$, holding other variables constant" (Bilder and Loughin 2014; Agresti and Kateri 2011). The interpretation of odds ratios for other levels of the separate models and for the joint model is in a similar manner.

9.3.2 Continuous Response Model for Post-Release Costs

Linear regression models were used, with costs as continuous response variables, and types and consequences of release, and two other factors as explanatory variables. The objective of estimation of these models was testing whether the types and consequences of release of crude oil significantly affect the post-release costs and quantifying the possible effects.

One issue with such a statistical approach for modeling costs of release incidents is the distributional assumptions of a regular linear regression (Normal error distribution) do not necessary hold, and a heavy-tailed error term distribution is expected (due to presence of numerous small and non-costly reported incidents as opposed to few very costly release incidents). One remedy is to remove influential observations from the data prior to model estimation. Another approach, termed "robust regression", is to use a fitting criterion that is not as vulnerable as least squares to influential data points (Fox and others 2002). While there are different methods for robust regression, the most common type is M-estimation, which can be considered as a generalization of the ML estimation (Fox and others 2002). This approach was utilized in this chapter and was implemented by the iterated re-weighted least squares. More information and details are available in (Huber 2011; Hampel et al. 2011).

9.4 Data and Variables

Similar to chapter 8, ten-year data (2007-2016) of crude oil release incidents from trains in the U.S. was extracted from the PHMSA database using the Incident Reports Database Search tool (Pipeline and Hazardous Materials Safety Administration and Office of Hazardous Materials Safety 2018). PHMSA incident data description and reporting criteria are available in section 8.3. Missing values in the variables that were used in the modeling resulted in less than 3.8% decrease in the dataset's size, leading to a final set of 638 tank cars.

Table 9.1 presents the variables and their respective statistics. The *bakken* variable indicated whether the crude oil was shipped from the Bakken region and should have been categorized as Bakken light sweet crude oil or not. This variable was formed based on the origin state of the shipment (North Dakota or Montana). The packing group information was available in the dataset. Packing group I, II and III represent great, medium and minor danger, respectively. The criteria for assigning packing group for crude oil is based on flash point and initial boiling point of the crude oil, that shippers should obtain through laboratory tests (*Class 3-Assignment of Packing Group* 2010). Information regarding tank head puncture resistance system and tank insulation was extracted from the tank car specification marking (*Specifications for Tank Cars* 2012), that was available in the dataset. Tank head puncture resistance system is capable of sustaining coupler-to-head impacts of the relative speed of 18 mph, usually accomplished by the installation of separate head shields or full-head tank jackets made of 1/2-inch-thick steel on each end of the tank car (Allen D. Maty 2017). Tank insulation is used to moderate the temperature of crude oil during transportation (Allen D. Maty 2017).

FRA provides the definition of Non-Accident Releases (NARs) as: "*the unintentional release of a hazmat while in transportation, including loading and unloading while in railroad possession, that is not caused by a derailment, collision or other rail related accident. NARs consist of leaks, splashes, and other releases from improperly secured or defective valves, fittings, and tank shells, and include venting of non-atmospheric gases from safety relief devices.*" NARs were detected in the data based on the provided narrations.

Table 9.1 Variables and Their Statistics

Variable	Names	Values and Statistics
Response Variables		
Type of Release	type	Spillage (86.21%), Gas Dispersion (08.93%), Both (04.86%)
Consequence of Release	cons	Fire (07.21%), Explosion (07.21%), None (85.58%)
Joint Type and Consequence of Release	typecons	Spillage and None (71.79%), Spillage and Fire (07.21%), Spillage and Explosion (07.21%), Gas Dispersion and None (08.93%), Both and None (04.86%)
Explanatory Variables		
Bakken Crude Oil	bakken	0 = No (51.72%), 1 = Yes (48.28%)
Packing Group	pack.group	I (51.88%), II (30.41%), III (17.71%)
Tank Head Puncture Resistance System	punc.res	0 = No (90.28%), 1 = Yes (09.72%)

Tank Insulation	insulated	0 = No (95.45%), 1 = Yes (04.54%)
Tank Design Pressure (psi)	dsgnpress	mean = 107.97, variance = 3207.14
Quantity Released (gallon)	quant.rel	mean = 2994.55, variance = 56620119
Non-Accident Release (NAR)	nar	0 = No (20.53%), 1 = Yes (79.47%)

Similar to chapter 8, post-release costs, available in the dataset, included carrier/property damage, response/clean-up costs, evacuation costs, injuries/fatalities, and roadway closure (costs of evacuation were assumed $250.00 per person-day (Saat et al. 2014), monetary costs of not-hospitalized injury as the only type of injury/fatality that occurred in the dataset was assumed $62500.00 per injury (Iranitalab and Khattak 2017), and roadway closure was assumed to cost $218,000.00 per day (Erkut, Tjandra, and Verter 2007; Mallela and Sadavisam 2011)). The minimum, maximum, mean and standard deviation of the costs were $0.00, $25,330,322.00, $146,792.00 and $1,365,787.00, respectively.

9.5 Modeling Results

This section presents the estimated statistical models. These include multinomial regressions capturing the impacts of crude oil, tank car design and incident characteristics on types and consequences (separately and jointly) of release of crude oil in a train incident and a robust linear regression model quantifying the effects of type and consequence of release of crude oil on the post-release costs.

9.5.1 Models for Types and Consequences of Release

The variables used in each model and the p-values of the LR tests are presented in Table 9.2. Variable selection was performed using LR test and AICc (Bilder and Loughin 2014; Agresti and Kateri 2011).

Table 9.2 p-values of the LR Test in the Release Type and Release Consequence Models

Variables		Separate				Joint	
		Type of Release		Consequence of Release		Type and Consequence of Release	
Crude Oil Characteristics	bakken	0.00062	***	0.09105	.	0.00181	**
	pack.group	0.00101	**	0.00000	***	0.00000	***
Tank Car Characteristics	punc.res	0.00000	***	0.07486	.	0.00000	***
	insulated	0.00198	**	—		0.01316	*
	dsgnpress	0.48524		—		—	
Incident Characteristics	nar	0.00000	***	0.00000	***	0.00000	***
	quant.rel	NA		0.00000	***	0.00000	***

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

—: Not Used, NA: Not Applicable

Point estimates of the odds ratios and their 95% CI for the release type with "spillage" as the base level are presented in Table 9.3. With 95% confidence and subject to keeping all the other variables (rather than the variable being interpreted) constant, the model interpretations are as follows. The odds of gas dispersion vs. spillage, and both types of release vs. spillage change by an amount between 0.29 to 0.98 times, and 0.05 to 0.55 times, respectively, for the light sweet crude oil from Bakken region. Packing group II decreased the odds of gas dispersion vs. spillage by 0.14 and 0.64 times relative to packing group I. These values were estimated as 0.08 to 0.84 for packing group III. Equipment of tank cars to puncture resistance system changed the odds of gas dispersion vs. spillage by an amount between 2.35 to 9.70 times, and both release types vs. spillage by an amount between 4.49 to 33.67 times. Insulation of the tank cars increased the odds of both release types vs. spillage only by 2.58 to 20.26 times. The odds of gas dispersion vs. spillage were increased by an amount between 1.74 to 466.39 times, for NARs. Other than these effects, there was no sufficient evidence on the impacts of explanatory variables on the types of release.

Table 9.3 Values of c, Point Estimates of Odds Ratios and Profile LR Confidence Intervals for Odds Ratios in Release Type Models

Variables		c	Gas			Both (Gas and Spillage)		
			Point Estimate	95% CI Lower Bound	95% CI Upper Bound	Point Estimate	95% CI Lower Bound	95% CI Upper Bound
Crude Oil Characteristics	bakken	1	**0.53**	**0.29**	**0.98**	**0.17**	**0.05**	**0.55**
	pack.groupII	1	**0.30**	**0.14**	**0.64**	1.09	0.41	2.85
	pack.groupIII	1	**0.27**	**0.08**	**0.84**	2.10	0.77	5.74
Tank Car Characteristics	punc.res	1	**4.77**	**2.35**	**9.69**	**12.30**	**4.49**	**33.67**
	insulated	1	1.32	0.37	4.69	**7.23**	**2.58**	**20.26**
	dsgnpress	25	0.97	0.80	1.18	0.93	0.77	1.13
Incident Characteristics	nar	1	**28.51**	**1.74**	**466.39**	11.01	0.62	195.69

Table 9.4 presents the odds ratios and 95% CI’s for the consequences of crude oil release model, with “none” as the base level. With 95% confidence and holding all the other variables except the variable being interpreted constant, it can be said that packing group II, relative to packing group I increased the odds of explosion vs. no release consequence by an amount between 1.61 to 158.93 times. There was no sufficient evidence towards the existence of any impacts of packing group II on fire and packing group III on fire and explosion, relative to packing group I. NARs, relative to accident releases, decreased the odds of fire and explosion vs. no consequence, by amounts between less than 0.01 to 0.11 times, and less than 0.01 and 0.06 times, respectively. The odds of fire and explosion vs. no release consequence in a crude oil release incident increased for every 1000-gallon increase in quantity of release of crude oil by a percentage between 13.69% to 37.56% and 12.96% to 37.91%, respectively. Sufficient evidence was not available to support the existence of any effects of Bakken region crude

oil, tank head puncture resistance system, tank car insulation and tank car design pressure on fire or explosion.

Table 9.4 Values of c, Point Estimates of Odds Ratios and Profile LR Confidence Intervals for Odds Ratios in Release Consequence Models

Variables		c	Fire			Explosion		
			Point Estimate	95% CI Lower Bound	95% CI Upper Bound	Point Estimate	95% CI Lower Bound	95% CI Upper Bound
Crude Oil Characteristics	bakken	1	4.04	0.58	28.34	14.39	0.47	436.77
	pack.groupII	1	0.52	0.05	5.50	**15.98**	**1.61**	**158.93**
	pack.groupIII	1	0.48	0.07	3.06	0.08	0.00	2.40
Tank Car Characteristics	punc.res	1	5.56	0.86	35.96	0.79	0.03	21.21
	insulated	1	—	—	—	—	—	—
	dsgnpress	25	—	—	—	—	—	—
Incident Characteristics	nar	1	**0.02**	**0.00**	**0.11**	**0.00**	**0.00**	**0.06**
	quant.rel	1000	**1.25**	**1.14**	**1.38**	**1.25**	**1.13**	**1.38**

—: Not Used

Table 9.5 presents the odds ratios and 95% CI's for the joint model of type and consequences of crude oil release, with "spillage and none" as the base level. Again, with 95% confidence and holding all the other variables except the variable under interpretation constant, Bakken crude oil decreases the odds of simultaneous spillage and gas dispersion with no consequences vs. spillage with no consequences by an amount between 0.07 to 0.58 times. Packing group II, relative to packing group I, increased the odds of spillage and explosion vs. spillage and no consequences by an amount between 1.70 to 138.33 times, while it decreased the odds of gas dispersion and no consequences vs. spillage and no consequences by 0.14 to 0.65 times. Packing group III, relative to packing group II, decreased the odds of gas disperse and none vs. spillage and none by an amount between 0.07 to 0.66. Equipment of tank cars to puncture resistance system increased the odds of gas dispersion with no consequences, and both types of release with no consequences vs. spillage with no consequences by amounts between 2.41 to 10.03 and 4.73 to 35.98 times, respectively. Insulation of the tank cars increased the odds of spillage and explosion vs. spillage with no consequences by an amount between 1.82 to 17146.04 times, while it increased the odds of both types of release and no consequences by 2.87 to 22.31 times. The odds of spillage with fire, spillage with explosion, as opposed to spillage and no consequences for an NAR were decreased by amounts between less than 0.01 to 0.14 times and less than 0.01 and 0.06 times, respectively. A 1000-gallon increase in the amount of released crude oil increased the odds of spillage with fire, and spillage with explosion vs. spillage with no consequences by amounts between 12.88% to 36.17% and 12.13% to 36.38%, respectively.

Table 9.5 Values of c, Point Estimates of Odds Ratios and Profile LR Confidence Intervals for Odds Ratios in Release Consequence Models

Variables		c	Spillage and Fire			Spillage and Explosion		
			Point Estimate	95% CI Lower Bound	95% CI Upper Bound	Point Estimate	95% CI Lower Bound	95% CI Upper Bound
Crude Oil Characteristics	bakken	1	3.31	0.47	23.20	19.99	0.56	719.82
	pack.groupII	1	0.48	0.05	4.55	**15.33**	**1.70**	**138.33**
	pack.groupIII	1	0.45	0.08	2.66	0.04	0.00	1.67
Tank Car Characteristics	punc.res	1	5.94	0.92	38.16	0.82	0.03	23.04
	insulated	1	1.85	0.02	154.96	**176.68**	**1.82**	**17146.04**
	dsgnpress	25	—	—	—	—	—	—
Incident Characteristics	nar	1	**0.03**	**0.01**	**0.14**	**0.00**	**0.00**	**0.06**
	quant.rel	1000	**1.24**	**1.13**	**1.36**	**1.24**	**1.12**	**1.36**
Variables		c	Gas Dispersion and None			Both and None		
			Point Estimate	95% CI Lower Bound	95% CI Upper Bound	Point Estimate	95% CI Lower Bound	95% CI Upper Bound
Crude Oil Characteristics	bakken	1	0.55	0.29	1.02	**0.18**	**0.06**	**0.58**
	pack.groupII	1	**0.30**	**0.14**	**0.65**	1.12	0.42	2.94
	pack.groupIII	1	**0.21**	**0.07**	**0.66**	1.74	0.64	4.73

Tank Car Characteristics	punc.res	1	**4.92**	**2.41**	**10.03**	**13.05**	**4.73**	**35.98**
	insulated	1	1.38	0.39	4.97	**7.99**	**2.86**	**22.31**
	dsgnpress	25	—	—	—	—	—	—
Incident Characteristics	nar	1	7.95	0.54	116.85	9.98	0.43	233.75
	quant.rel	1000	1.08	0.90	1.30	1.19	0.99	1.43

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
—: Not Used

9.5.2 Model for Post-Release Costs

A robust linear regression model was estimated at the incident level, using total costs as the response variables, and types of release and consequences of release as the explanatory variables. The point estimates and 95% CI’s for the estimated coefficients, along with LR test p-values and standard errors are presented in Table 9.6. LR test results and CI’s indicate there was not enough evidence in the dataset to show that variations in types of release affected the costs, directly. However, the estimated coefficients for fire and explosion, along with NAR variable and quantity released were statistically significant in the model. These variables changed damage costs by amounts between the upper and lower bounds of the CI’s reported in Table 9.6.

Table 9.6 95% CI's for the Damage Costs Robust Linear Regression Models (rounded to nearest $1)

Coefficients	Point Estimate	Standard Error	LR Test p-value		95% CI Lower Bound	95% CI Upper Bound
(Intercept)	253,274.38	936.22	—		251,439.42	255,109.33
Gas Dispersion	-291.41	454.96	0.52220		-1,183.12	600.30
Spillage	303.96	563.48	0.58990		-800.44	1,408.36
Fire	2,072,608.65	1205.57	0.00000	***	2,070,245.79	2,074,971.52
Explosion	13,529,080.97	2188.78	0.00000	***	13,524,791.03	13,533,370.91
NAR	-251,744.34	755.17	0.00000	***	-253,224.45	-250,264.23
Quantity Released	28,860.20	192.79	0.00000	***	28,709.20	29,011.26

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

9.6 Discussion and Conclusions

Sufficient evidence was not found in the data to show the light sweet crude oil of Bakken region significantly increased the probability of fire and explosion in case of release. Release of this type of crude oil was found less probable to lead to gas dispersion or simultaneous spillage and gas dispersion, relative to spillage. Therefore, the results of this chapter statistically cannot confirm PHMSA’s safety alert regarding the possibility of Bakken crude oil being more flammable than traditional heavy crude oil or other light sweet crude oil. While, in case of release, this type of crude oil is more probable to spill rather than disperse as gas, there was no sufficient evidence that spillage is costlier than gas dispersion, according to the costs model. So, evidence in this data do not support the hypothesis that transportation of Bakken crude oil by rail results in a different degree of risk, relative to other types of crude oil moved by rail in the U.S.

The crude oil categorized as packing groups II (medium danger) and III (minor danger) decreased the probability of gas dispersion, and packing group II increased the probability of explosion, relative to crude oil packing group I (great danger). This might be due to possible inaccuracies in results of flash point and initial boiling point tests, or effects of other potential important variables that were not considered in this study. This finding was consistent with one of the findings of Lord et al. (David Lord et al. 2015), the inadequacy of current methods for assignment of crude oil transportation hazard classification and packing group. Based on these results, safety-related decisions solely based on packing groups are not suggested.

Tank car head puncture resistance system and tank car insulation were not found to be directly associated with probability of fire or explosion (except for the ignorable case of insulation and explosion in the joint model with an unusually wide CI, possibly due to small variation in the variable values), but they increased the likelihood of gas dispersion. The danger crude oil-carrying trains expose to the populations near railroads due to toxic gas dispersion, and a corresponding possible explosion with no time for evacuation (although not observed in the data but an example is the Lac-Mégantic rail disaster in Canada) is not negligible. So, based on the results, the use of such tank cars is not recommended for crude oil-carrying trains that pass though residential areas, while they may be preferred in other routes, since far from population gas dispersion may be preferred to spillage, due to generally lower probability of fire and explosion.

For each thousand-ton increase in quantity of crude oil spillage, the probability of fire, explosion and total costs increased, significantly. This can be considered in terms of the quantity of crude oil that is loaded in each tank car, especially the tank cars with fewer safety design features, or tank cars with higher propensity to derail in an incident, depending on their position in a train (Saccomanno and El-Hage 1991, 1989; Liu, Saat, and Barkan 2014). NARs were associated with higher probability of gas dispersion, and lower probability of fire and explosion. Due to significantly smaller quantities of crude oil release in these releases, compared to accident-caused releases, they are generally less hazardous, and according to the costs models, they cause approximately 250 thousand dollars less than other releases on average. Countermeasures regarding prevention of such releases, e.g. regular and frequent inspection of valves, can be prioritized for implementation based on the corresponding costs and benefits. Regarding the costs model, decision-makers may consider how the consequences of release of crude oil from trains affect damage and recovery costs. A more expensive countermeasure that is likely to prevent explosions more efficiently may be preferred over a less costly countermeasure that performs better towards fire prevention, despite its extra costs. The estimated costs that these release consequences cause should be considered in a cost-benefit analysis for decision-making.

The results of the joint and separate models were consistent, and the magnitudes and directions of the odds ratios were relatively similar. Both approaches provided informative outcomes, useful in inference, and interpretation of the relationships between the explanatory and response variables. The differences in the results of the joint and separate approaches indicated how using a joint modeling framework for types and consequences of crude oil release from trains to account for the possible interdependence between these two variables was informative. However, estimation and interpretation of only the separate models assuming no correlation between the two response variables could be sufficient with regards to the general results and conclusions. As was mentioned in chapter 8, reduction in number of rail-based crude oil release incidents does not affect the importance of this study because of similar reasons.

One limitation of this chapter was the unavailability of other potentially important variables in the dataset, including other tank car and release characteristics. Some of these variables were available in the dataset, but due to large proportion of missing values, were not used in this study (such as causes of release, tank cars capacity, amount of material in tank cars, age of tank cars, material of construction, shell and head thickness, train speed, and weather conditions). This may have caused bias in the results, conclusions and recommendations of this chapter due to unobserved heterogeneity and should be considered in practice. Besides fire and explosion, entering a waterway/sewer system and environmental damage were the other two reported consequences of release of crude oil in the dataset. However, they were not considered in this study, since they are not independent of the environment where the release occurred, and the environmental information was not available in the dataset.

For future studies, researchers may address the mentioned limitations of this chapter by obtaining datasets that are more comprehensive, in terms of safety design of tank cars, release details, and environmental characteristics. Other modeling techniques and data analysis approaches may be applied to crude oil release data, which might uncover other useful findings. Similar modeling approaches can be utilized for investigating types and consequences of other hazmat releases from different modes of transportation, such as trucks and pipelines.

CHAPTER 10 SUMMARY, CONCLUSIONS AND FUTURE RESEARCH

This chapter provides a summary of the research and the conclusions of each of the six area foci of this dissertation, followed by recommendations for future studies.

10.1 Train-Level and Car-Level Modeling of Hazardous Materials Release in Railroad Incidents

This effort quantified the impacts of incident type, railroad, environment and train/car characteristics on the probability of hazmat release in a hazmat-carrying train incident and provided a prediction tool for hazmat release. Two sets of models utilized the FRA 2012-2016 rail equipment incident dataset. The units of analyses for these two sets were trains and hazmat cars. Logistic regression and mixed logistic regression were investigated to account for hazmat release and potential single-level and two-level grouping in the data (due to possible hazmat release interdependence among hazmat cars belonging to a train and trains belonging to an incident). Development of ROC curves improved the prediction performance of the models by defining an appropriate cut-off point.

Results showed that derailment increased hazmat release probability more than other incident types. Incidents due to signal and communication causes were most likely to result in hazmat release. Higher proportion of damaged/derailed hazmat cars and proportion of hazmat cars in a train, track classes 2 and 3, higher train speed, and train gross tonnage were the other important factors. Results of mixed models showed hazmat release from cars belonging to a train were interdependent and hazmat release from trains belonging to an incident were independent. While models at both levels led to useful results, car-level models had better prediction performance.

Future studies may utilize other explanatory variables to investigate their effects, such as hazmat car specification and safety design, and type of hazmat on the hazmat release probability. This requires the use of a more comprehensive train incident data. The effects of incident causes on hazmat release at a more detailed level in train incidents can be the emphasis of a future study.

10.2 Rollover and Hazardous Materials Release Models for Cargo Tank Truck Crashes

CTTs are one of the major surface transportation carriers of hazmat in the U.S. CTT's rollover crashes are the leading cause of injuries and fatalities from hazmat transportation incidents. CTTs are susceptible to rollover crashes due to their size, distribution of weight, a higher center of gravity, and the surging and sloshing of liquid cargo during transportation. This endeavor concentrated on identification and quantification of the effects of various factors on the probability of rollover and release of hazmat in CTT-involved crashes, and developing a prediction tool for these probabilities. BMA-based logistic regression models were estimated with rollover and hazmat release as the binary response variables, and crash, trucks, roadway, environment, and driver characteristics as the explanatory variables. States of Nebraska and Kansas 2010-2016 police reported crash data were combined and filtered for CTT-involved crashes and used in modeling.

Salient results were: non-collision crashes were more likely to result in rollovers; side impacts to CTTs and severe crosswinds increased the likelihood of rollovers; heavier and older trucks were more prone to rollovers; tractor and semi-trailer decreased the probability of rollover compared to all other body styles; and collisions with objects and higher posted speeds increased rollover probability. Rollover and involvement of intersections in the crash increased the likelihood of hazmat release. ROC curves indicated substantial prediction performance for both models, and ensured appropriateness of the modeling approach for inference on the crash dataset.

Future studies may attempt to use more comprehensive datasets that include other explanatory variables that could potentially affect probabilities of rollover and hazmat release, such as more detailed driver and CTT characteristics, crash speed, type and amount of loaded hazmat, etc. Utilizing other modeling methods and algorithms for inference and prediction may uncover additional useful information in future studies. While CTTs are one of the major truck carriers of hazmat, other types of trucks are also used for this matter. Similar investigation may be considered for those trucks.

10.3 Modeling the Probability of Hazardous Materials Release at Highway-Rail Grade Crossings

Crashes at HRGCs that involve a truck or a train carrying hazmat expose people and the environment to the potentially severe consequences of hazmat release. This research involved statistical modeling of the probability of hazmat release from trucks and/or trains in crashes at HRGCs to identify factors associated with hazmat release. The FRA HRGC crash dataset (2007-2016) yielded two subsets of crashes: 1) those involving hazmat-carrying trucks and 2) those involving hazmat-carrying trains.

Results from a logistic regression model using data subset 1 (crashes involving hazmat-carrying trucks) with hazmat release/no release as the response variable showed that standard flashing signal lights, railroad crossbucks, and railroad classes II and III (relative to railroad class I) were associated with lower hazmat release probability from hazmat-carrying trucks. Hazmat release probability from trucks was higher with freight train involvement. Results from a logistic regression model using data subset 2 (crashes involving hazmat-carrying trains) revealed that hazmat release probability from trains was lower with warmer temperature. However, the probability of release from trains was greater with railroad class II (relative to railroad class I), type of highway user (different types of trucks and motorcycle relative to automobiles) and weather conditions (fog, sleet or snow, relative to clear). A comparison of the results from this study with HRGC crash severity studies highlighted the importance and usefulness of this study.

For future studies, researchers may use other HRGC crash data that include other potentially important explanatory variables, e.g. details about HRGC control devices, actions of highway users during crashes, sight obstructions, type of hazmat, roadway conditions, etc. Different modeling approaches may be utilized for analyzing hazmat-related crashes at HRGCs that might lead to further insights. Short-term and long-term costs and damages of hazmat release at HRGCs may be studied to prioritize countermeasures and policies regarding public safety improvements at HRGCs.

10.4 Prediction of Hazardous Materials Release In Train Incidents and Cargo Tank Truck Crashes

Quantifying conditional probability of release of hazmat from trains in rail incidents and CTTs in highway crashes is an important component of hazmat transportation risk as it assists safety agencies and shippers in decision-making. The objective of this focus was identifying computational tools with reliable performance for quantifying probability of hazmat release in train incidents as well as CTT crashes. Hazmat release (release or no release) was classified by statistical and machine learning methods (logistic regression, naïve Bayes, RF, and SVM) using available and relevant explanatory variables. The datasets were FRA rail equipment incident data, and combined Nebraska and Kansas police reported traffic crash data.

The results were compared based on precision, recall and area under ROC curves (AUC). RF had the best performance in classifying hazmat release for trains and railcars in almost all cases, based on different criteria. For CTTs, SVM and RF had the highest precision, while logistic regression and naïve Bayes performed better based on recall. Naïve Bayes had the highest AUC. The research provided recommendations regarding usage of the classifiers and regressors depending on the purpose of analysis.

For future studies, using other incident/crash datasets may address limitation of datasets of this focus, in terms of geographic diversity and potentially important explanatory variables. Other classifiers and regressors may be applied to the hazmat release problem and the results can compare to this study. Classification methods of this study can be implemented to the other components of hazmat risk, such as incident/crash frequency and release consequences in the future studies.

10.5 Modeling of Frequency and Aggregate Measures of Severity of U.S. Rail-Based Crude Oil Release Incidents

Trains transport a large portion of produced crude oil to the refineries in the U.S. This potentially exposes people living near railways and the proximate environment to the ill effects of incidents resulting in crude oil release. The objective of this focus was to identify and quantify the effects of volumes and distances of rail-based crude oil transport and other macroscopic-level variables on the frequency and severity of crude oil release incidents. An optimization problem was formulated to approximate state-to-state volume of crude oil movement based on higher-level production-consumption data. Four mixed-effects origin-destination based statistical models were estimated for rail-based crude oil release incidents: one model for frequency and three models for measures of aggregate severity (number of released tank cars, quantity released, and total costs). State-to-state volume of crude oil movement, transport distance, availability of other modes of transportation and number of class I railroad companies served as explanatory variables.

Results provided useful insights for policy-makers and shipping companies. Some of the findings include: increase in volume of crude oil shipped from one state to another, up to a point, led to greater frequency and severity of incidents between the two states; for each 100-mile increase in the distance of crude oil shipment, the frequency of incidents increased by 14.01%; there was lack of evidence for existence of any impacts from availability of other modes of transportation on the response variables, while the number of class I railroad companies significantly affected frequency and number of released tank cars.

Future studies may focus on modeling frequency of crude oil-carrying train incidents, regardless of releasing the crude oil, and modeling the probability of release of crude oil, given an incident, separately. This approach can provide the effects of microscopic factors, such as characteristics of crude oil, train, railroad, etc., on occurrence of crude oil release incidents. Such a study requires a dataset of crude oil-carrying train incidents. The use of other statistical methods for modeling or machine learning methods for better prediction performance may also be investigated.

10.6 Joint and Separate Modeling of Types and Consequences of Rail-Based Crude Oil Release Incidents

The main objectives of this focus were identification of the factors that affect the types and consequences of crude oil release from trains, quantification of these effects, and investigation of the impacts of types and consequences of crude oil release on the resulting costs and damages. The factors considered as potentially affecting types and consequences of release included characteristics of crude oil, tank cars, and release incidents. Two separate multinomial response models for types of crude oil release (gas dispersion, spillage and both) and consequences of crude oil release (fire, explosion and none), and one joint multinomial response model were estimated using 2007-2016 PHMSA crude oil release data. Estimated robust linear regression models captured the effects of the types and consequences of release on post-release costs.

Results showed that non-accident releases were associated with higher probability of gas dispersion, lower probability of fire and explosion, and lower costs. Tank car head puncture resistance system and tank car insulation did not directly affect the probability of fire or explosion, but they increased the probability of gas dispersion. For each thousand-ton increase in quantity of spillage, the probability of fire and explosion increased significantly. While sufficient evidence was not found in the data indicating a relationship between types of crude oil release and post-release costs, fires and explosions prominently increased these costs.

For future studies, researchers may consider using more comprehensive rail-based crude-oil release incident data, in terms of availability of characteristics of design of tank cars, details of release, and environmental characteristics. Other modeling techniques and data analysis approaches may be applied to crude oil release data, which might uncover other useful findings. Similar modeling approaches can be utilized for investigating types and consequences of other hazmat releases from different modes of transportation, such as trucks and pipelines.

10.7 Summary of Objectives and Achievements

This study had two main objectives. The first one was identification and quantification of the effects of different factors on occurrence and consequences of hazmat-related incidents, towards identifying effective policies and countermeasures for improving safety. Chapters 4, 5, 6, 8, and 9 were fully or partially devoted to this objective. Contributing factors to the conditional release of hazmat from trains and trucks were identified and the magnitude of their effects on hazmat release was estimated in chapters 4, 5, and 6. Chapter 8 had a macroscopic perspective, with the objective of identifying the factors that affect frequency and severity of crude oil release from trains, while chapter 9 took into account the contributing factors to the consequences of crude oil release from trains. Each of the above studies were able to provide effective policies and countermeasures for safety improvement.

The second objective of this study was quantifying components of risk of hazmat transportation for costs prediction, planning purposes, or short-term decision-making. While chapter 7 was completely devoted to this objective, the estimated models in the other chapters were useful for this objective as well. The model-based and non-model-based methods that were utilized in this study were able to estimate some components of hazmat transportation risk, including conditional probability of hazmat release in rail incidents, CTT crashes, and HRGC crashes, frequency and aggregate severity of rail-based crude oil release incidents, and probability of types and consequences of crude oil release from trains.

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