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Risk Analysis of Freight Train Collisions in the United States, 2000 to 2014

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ABSTRACT

Train accidents damage infrastructure and rolling stock, disrupt operations, and may result in casualties and environmental damage. While the majority of previous studies focused on the safety risks associated with train derailments or highway-rail grade crossing collisions, much less work has been undertaken to evaluate train collision risk. This paper develops a statistical risk analysis methodology for freight-train collisions in the United States between 2000 and 2014. Negative binomial regression models are developed to estimate the frequency of freight-train collisions as a function of year and traffic volume by accident cause. Train collision severity, measured by the average number of railcars derailed, varied with accident cause. Train collision risk, defined as the product of collision frequency and severity, is predicted for 2015 to 2017, based on the 2000 to 2014 safety trend. The statistical procedures developed in this paper can be adapted to various other types of consequences, such as damage costs or casualties. Ultimately, this paper and its sequent studies aim to provide the railroad industry with data analytic tools to discover useful information from historical accidents so as to make risk-informed safety decisions.

INTRODUCTION

The American economy hinges on freight railroads, which transport around 40 percent of ton-miles of cargo [1]. In the meantime, train accidents damage infrastructure and rolling stock, disrupt operations and may cause casualties and environmental damage. There are three major accident types on U.S. freight-railroads: derailment, collision, and highway-rail grade crossing collisions. There is extensive research on derailment risk analysis [2 - 12] and highway-rail grade crossing safety [13-15]. However, less work has been undertaken to evaluate train collision risk. To our knowledge, few published studies are dedicated to statistical risk analysis of U.S. freight-train collisions. This knowledge gap motivates the development of this paper, which aims to address the following research inquires:

1) How can train collision risk be quantified?
2) How does train collision risk vary with time, traffic exposure, type of track, and accident cause?
3) How can collision risk be predicted?

DATA SOURCES

The Federal Railroad Administration (FRA) of the US Department of Transportation (USDOT) requires railroads operating in the U.S. to submit detailed reports of accidents whose damage costs to track infrastructure, rolling stock signals exceeded a specified monetary threshold [16]. The FRA compiles the submitted accident reports into a Rail Equipment Accident (REA) database. The REA database contains useful information regarding the type of railroad (e.g., freight railroad, passenger railroad), the type of accident (e.g., derailment, collision, grade crossing collision, etc.), type of track (mainline, yard, siding, industrial), accident cause (e.g., track failures, mechanical failures, human errors) and accident consequences (e.g., number of railcars derailed, track and rolling stock damage costs, casualties), and other accident circumstances. The FRA REA database has been used in many previous studies [2-4, 12, 17]. In addition to accident data, the railroads also report their monthly train-mile data through the FRA Operational Database. These data sources can be integrated and used to model freight-train collision risk. Note that each railroad carrier may also have its internal accident database that contains the accidents that need not be reported to the FRA because their damage costs are below the FRA reporting threshold. The Non-FRA-reportable accidents are typically not publicly available, and thus are excluded from the analysis.

RESEARCH OBJECTIVES AND SCOPE

This paper aspires to make the best use of historical FRA-reportable freight-train collision data to understand major collision causes and the temporal change in train collision risk. The risk analysis will ultimately inform decision makers in the process of data-driven safety policy development. Specifically, this research aims to attain the following deliverables:

- Develop a quantitative methodology for freight-train collision risk analysis
- Develop statistical procedures and toolboxes for modeling the frequency and severity of freight-train collision by influencing factors
- Project future train collision risk based on the current safety trend. The risk projection provides a scientific basis for evaluating the safety benefit of prospective collision avoidance technologies

The majority of train accidents occur on Class I railroads [6]. Each Class I railroad has annual operating revenue exceeding $478.5 million (2014 dollars). Class I railroads accounted for approximately 68% of U.S. railroad route miles, 97% of total ton-miles transported, and 94% of the total freight rail revenue [18]. Therefore, this paper focuses on Class I railroad freight-train collisions from 2000 to 2014. Depending on questions of interest and data availability, the methodologies can be adapted to other types of train accidents.

This paper is structured as follows. First, some key definitions are presented to clarify the scope of this analysis. Second, statistical models are developed to estimate collision frequency as a function of year and traffic volume, by the type of track and accident cause. Third, collision severity (measured by the average number of railcars derailed per train collision) is estimate based on historical accident data. Fourth, future train collision frequency and severity are projected based on the 2000 to 2014 safety trend. Finally, the paper discusses the implications of the analyses with respect to research and practice.

DEFINITIONS

Collision. According to the FRA, a collision is defined as "an impact between on-track equipment consists while both are on rails and where one of the consists is operating under train movement rules or is subject to the protection afforded to trains." [16] This definition includes instances where a portion of a train occupying a siding is fouling the mainline and is struck by an approaching train. In the FRA REA database, there are six types of collision: head-on, rear-end, side, raking, broken train, and railroad crossing. A head-on collision occurs when the trains or locomotives involved are traveling in opposite directions on the same track. A rear-end collision occurs when the trains or locomotives involved are traveling in the same direction on the same track. A side collision occurs at a turnout where one train strikes the side of another train. A raking collision occurs between the parts or lading of a train on an adjacent track, or with a structure such as a bridge. A broken train collision occurs when a moving train breaks into parts and an impact occurs between these parts, or when a portion of the broken train collides with another train. A railroad crossing collision occurs between on-track railroad equipment at a point where tracks intersect [16]. In this paper, the type of equipment is freight train.

Safety. Safety can be defined as the number of accidents, evaluated by kind and severity, which are expected to occur on the entity during a specified period [19]. Liu provides a theoretical explanation to this definition from a stochastic process perspective. One highlight of this notion is "expected to occur." The difference between the observed and expected number of accidents represents the statistical uncertainty of accident occurrence [12]. The expected rate of accident frequency or severity of an accident can be estimated using multivariate regression techniques, which will be detailed later.

Risk. The risk can be defined as the likelihood and consequence of an accident [20]. In practice, researchers sometimes use the expected consequence to measure the risk. [4, 7, 8]. For example, if the accident consequence is measured by damage cost, the risk is interpreted by the expected (average) damage cost.

The above-mentioned definitions are the basis of the following statistical analyses. Depending on the questions of interest and data availability, analysts may choose to use alternative definitions. If so, they could adapt this paper's methodology accordingly.

The analyses in this paper focus on the collisions between freight trains, as well as the collisions between freight trains and non-train consists, such as maintenance vehicles, cut of cars, and locomotives. However, this paper excludes the collisions between freight trains and passenger trains. This type of collisions needs to account for both freight and passenger train operations and their possible interactions. Modeling this type of freight-and-passenger train collision may require a separate research study in the future.

STATISTICAL METHODOLOGY FOR TRAIN COLLISIOIN RISK ANALYSIS

Four types of track are recorded in the FRA REA database: main, siding, yard, and industrial tracks. These track types are used for different operational functions and consequently have different accident types, causes, and consequences [6]. Train accidents are categorized into derailment, collision, highway–rail grade crossing collision, and several other less frequent types. Liu et al. (2012) presents an analysis of train derailment frequency and severity by the type of track and type of accident using data from 2000 to 2010 [6].

The FRA REA database records over three hundred accident cause codes. Each cause code describes a specific accident circumstance. The train accident cause codes are hierarchically organized and categorized into major cause groups: track, equipment, human factors, signal, and miscellaneous [16]. Within each cause group, FRA organizes individual cause codes into subgroups of related causes, such as roadbed and track geometry, within the track group and similar subgroups within the other major cause groups. A variation on the FRA subgroups was developed by Arthur D. Little (ADL), in which similar cause codes were combined into groups on the basis of expert opinion [21]. The ADL groupings are similar to FRA's subgroups but are more fine-grained for certain causes, thereby allowing greater resolution in some cases. For example, the FRA grouping combines broken rails, joint bars, and rail anchors in the same subgroup, whereas the ADL grouping distinguishes between broken rail and joint bar defects [2]. These groups were used to analyze cause-specific collision frequency and severity. Note that the ADL accident cause grouping might not be the only grouping approach. Additionally, the same cause may fall into multiple groups. Therefore, if analysts use a different accident cause grouping scheme, the analyses should be adapted accordingly.

According to Fig. 1., on main tracks (including siding tracks thereafter), failure to obey or display signals and violation of train speed rules are the top two collision causes, whereas on yard tracks (including industrial tracks thereafter), violation of switching rules is the top cause group. A detailed breakdown of the cause codes within each ADL cause group can be found in ADL [21].

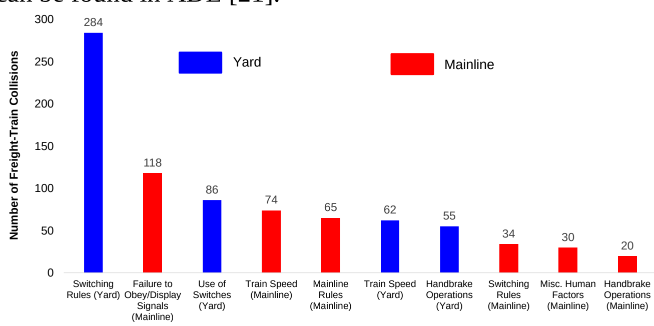

Figure 1. Top collision cause group (ADL cause group) on mainline and yard tracks, Class I freight railroads, 2000 to 2014

Model Development

A statistical model is developed to correlate train collision frequency with influencing factors. Based on data availability from the FRA REA database, this paper focuses on two potential affecting factors: year and annual traffic exposure. The "year" variable tests whether there is a temporal change of train collision frequency given traffic exposure. The "traffic exposure" variable describes whether and how train collision count varies with traffic volume in a given year. A basic model structure is as follows:

$$\mu_i = \exp(\alpha+\beta \times T_i+\theta \times M_i)M_i \quad (1)$$

where:

μ_i = expected number of freight-train collisions in year i
T_i = year (for example, T_i is 2000 for year 2000)
M_i = million train-miles in year i
α, β, θ = parameter coefficients

Collision rate is defined as the number of train collisions normalized by traffic exposure. According to this definition, Eq. (1). is re-written as:

$$Z_i = \mu_i / M_i = \exp(\alpha+\beta \times T_i+\theta \times M_i) \quad (2)$$

A similar model was used in several previous studies [12, 22-24]. Those studies assumed that train accident rate is independent of traffic exposure. In order to understand whether and how train collision frequency varies with traffic volume, our model generalizes the previous model by introducing a new parameter θ. $\theta > 0$ means that if traffic increases, collision rate would increase with traffic volume, given all else being equal. The previous model [12, 22-24] is a special case of the generalized model, given $\theta = 0$.

The next step is to estimate the unknown parameters based on historical data. The literature has numerous regression models, among which the negative binomial regression is used frequently. A technical review of the negative binomial model can be found in [25]. This paper starts with negative binomial regression. If the goodness of fit is inadequate, alternative models will be used. The negative binomial regression results for the two top causes on mainline tracks are presented in Table 1. The last column is the P-value of a parameter estimator, which represents the statistical significance of a predictor variable using the Wald Test [25]. A generally acceptable rule is that if a predictor variable has a P-value smaller than 5%, this variable is significant. The analysis found that for the cause of failure to obey or display signals, the parameter coefficient for the variable "year" is significantly negative (β = -0.0526; P = 0.0165), indicating that there is a significant temporal decline in train collision rate, given the traffic exposure.

Table 1. Negative binomial regression of train collision frequency, Class I freight railroads, top two mainline causes, 2000 to 2014 (only statistically significant predictor variables are displayed in the table)

Failure to obey or display signals on main tracks

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
α	101.2650	44.0028	5.30	0.0214
β	-0.0526	0.0219	5.74	0.0165

Deviance = 11.0, Degree of Freedom = 13, P = 0.85

Violation of train speed rules on main tracks

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
α	-9.8982	1.8406	28.92	<0.0001
θ	0.0096	0.0034	8.24	0.0041

Deviance = 9.57, Degree of Freedom = 13, P = 0.74

The goodness-of-fit of a negative binomial model can be evaluated using a statistical criterion called "Deviance." Statistical theory tells that the Deviance asymptotically follows a Chi Square distribution [25]. Based on this property, the P-value in the deviance test can be calculated. In general, if the P-value in the deviance test is larger than 5%, the model appears to be an adequate fit to the empirical data. In our example, the deviance are 11.0 and 9.57, the degree of freedom are both 13, and the corresponding P-value are 0.85, 0.74, respectively (Table 1). It indicates the negative binomial regression models fit the empirical data well for both causes. Based on the fitted parameters of significant variables, the expected frequency of U.S. freight-train collision which caused by failure obey or display signals and by violation of speed rules are estimated using the following equations:

Failure to obey or display signals

$$\mu_i = \exp(101.2650-0.0526T_i)M_i \quad (3)$$

Violation of speed rules

$$\mu_i = \exp(-9.8982+0.0096M_i)M_i \quad (4)$$

Table 2 compares the observed versus the predicted number of freight-train collisions using the negative binomial regression model described above.

Table 2. Empirical versus predicted freight-train collision frequency, two top causes on mainline tracks, 2000 to 2014

	Million	Failure to obey/display signals		Violation of train speed rules	
Year	Train-Miles	Observed Frequency	Estimated Frequency	Observed Frequency	Estimated Frequency
2000	524.93	8	11	5	4
2001	513.69	10	10	4	4
2002	534.14	8	10	3	5
2003	548.20	8	10	4	5
2004	570.37	13	10	10	7
2005	583.70	14	9	12	8
2006	599.89	8	9	8	10
2007	561.72	11	8	3	6
2008	542.66	7	7	6	5
2009	455.90	5	6	3	2
2010	488.35	4	6	3	3
2011	502.70	9	6	4	3
2012	513.11	5	6	2	4
2013	521.01	6	5	2	4
2014	534.52	2	5	5	5

In addition to the Deviance, another common goodness-of-fit test is the Chi-square test, which assesses the relative difference between each observation and estimation.

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \quad (5)$$

Where:

O_i = observed number of collisions in year i

E_i = estimated number of collisions in year i

n = sample size (number of years)

Based on Table 3, for the cause of failure to obey or display signals, χ^2 = 10.97. The corresponding P-value is 0.69 (degree of freedom is 14). For the cause of violation of train speed rule, χ^2 = 9.20. The corresponding P-value is 0.82 (degree of freedom is 14). Therefore, it indicates that the estimated collision frequency reasonably matches the observed count. Both the Deviance test and the Chi-square test show that a negative binomial regression model can be used to fit the empirical freight-train collision data in this paper.

COLLISION SEVERITY

In addition to collision frequency, severity is another important element in train collision risk analysis. This paper uses the average number of railcars derailed per freight-train collision as a proxy to measure collision severity. This metric is related to accident kinetic energy and has been extensively used in the prior work [2, 5-9]. A Wald–Wolfowitz runs test [26] was used to understand whether there is any significant temporal trend in collision severity. This statistical test checks if a data set results from a random process. When the P-value in the test is larger than 0.05, we may conclude that there is no statistically significant trend in terms of the average annual collision severity. Table 3 shows that the severities for the selected cause groups have no significant temporal trend. The yearly severity fluctuation is largely due to random variations.

Table 3. Number of railcars derailed per train collision, Class I freight railroads, top two collision causes, 2000 to 2014

Year	Failure to Obey/Display Signals	Violation of Train Speed Rules
2000	1.9	2.4
2001	19.0	2.8
2002	12.8	1.7
2003	8.0	8.3
2004	7.9	4.5
2005	5.6	4.8
2006	5.6	4.0
2007	7.2	0.7
2008	10.9	3.0
2009	5.2	0.7
2010	3.8	1.7
2011	5.4	0.5
2012	7.8	23.0
2013	17.8	0.0
2014	2.5	6.0
Average	8.1	4.3
Standard Error	1.3	1.5
P-value in Runs Test	0.46	0.16

COLLISION RISK ANALYSIS

Train collision risk can be defined as the product of collision frequency and severity:

$$R = F \times S \tag{6}$$

Where:
R = estimated annual collision risk
F = estimated annual collision frequency
S = estimated collision severity (number of railcars derailed per train collision)

Both the estimated frequency and severity are subject to statistical uncertainty. Correspondingly, there is uncertainty associated with the risk estimator. The variance of the risk estimator can be calculated using the following equation by assuming that the variances of the estimators of collision frequency and severity are independent. A statistical proof of the variance of two random variables can be found in Goodman [27],

$$Var(R) = Var(F \times S) = Var(F)Var(S) + Var(F)E(S)^2 + Var(S)E(F)^2 \tag{7}$$

Where:
Var(R) = variance of collision risk estimator
Var(F) = variance of collision frequency estimator
Var(S) = variance of collision severity estimator
E(F) = the estimator of collision frequency
E(S) = the estimator of collision severity

Furthermore, the 95% confidence interval of the collision risk estimator ($CI_{95\%}(R)$) is:

$$CI_{95\%}(R) = [R - 1.96\sqrt{Var(R)}, R + 1.96\sqrt{Var(R)}] \tag{8}$$

Based on Eq. (6). to (8)., the estimated annual collision risk and its 95% confidence interval is calculated (Table 4) using the average traffic volume between 2000 and 2014.

For example, if the traffic volume in 2017 is 533 million train-miles on Class I mainline, the projected collision frequency caused by failure to obey or display signals is around 5, with a 95% confidence interval of around 3 to 8. This projection entails a 95% chance that the actual number of collisions will be between 3 and 8. Collision risk, measured by the expected number of railcars derailed, is estimated to range between 14 and 59 in year 2017.

Table 4. Projected collision frequency, severity and risk in 2015 to 2017, top two collision causes on mainline tracks (future traffic volumes are assumed based on the average traffic volume from 2000 to 2014)

(a) Failure to obey or display signals on main tracks (declining collision rate by year)

		Collision Frequency			Collision Severity			Collision Risk		
Year	Million Train Miles	Mean	95% Lower Bound	95% Upper Bound	Mean	95% Lower Bound	95% Upper Bound	Mean	95% Lower Bound	95% Upper Bound
2015	532.99	5.0	3.3	7.7	8.1	5.5	10.7	41.0	18.0	63.0
2016	532.99	4.8	3.0	7.6	8.1	5.5	10.7	39.0	16.0	61.0
2017	532.99	4.5	2.7	7.5	8.1	5.5	10.7	37.0	14.0	59.0

(b) Violation of train speed rules on main tracks (no temporal effect on annual collision rate)

		Collision Frequency			Collision Severity			Collision Risk		
Year	Million Train Miles	Mean	95% Lower Bound	95% Upper Bound	Mean	95% Lower Bound	95% Upper Bound	Mean	95% Lower Bound	95% Upper Bound
2015	532.99	4.5	3.6	5.8	4.3	1.4	7.2	20.0	6.0	34.0
2016	532.99	4.5	3.6	5.8	4.3	1.4	7.2	20.0	6.0	34.0
2017	532.99	4.5	3.6	5.8	4.3	1.4	7.2	20.0	6.0	34.0

Notes:
(1) The 95% upper bound and lower bound of collision frequency were generated in a negative binomial regression model using GENMOD procedure in the statistical software SAS. It accounts for the variance-covariance matrix of parameter coefficient estimators. The algorithm for generating the confidence interval of the predicted value is presented in SAS Manual, Chapter 37 GENMOD procedure, page 1980.
(2) The 95% upper bound and lower bound of the estimated collision severity (number of cars derailed) was developed based on the sample mean and sample standard error of the annual collision severity between 2000 and 2014.
(3) It is assumed that collision severity (number of railcars derailed) does not vary with traffic volume
(4) The risk interval was developed using Eq. (7). & (8).

DISCUSSIONS

In this section, we discuss the contributions of this study with respect to the literature and practice. We also discuss the limitations of the current research due to data limit and suggest possible future research directions.

Contributions to the Literature

Since the FRA began to collect train accident data in the 1970s, researchers have an opportunity to look into historical accident data, discover useful information and propose risk-informed decisions. Compared with the highway safety community, where statistical modeling of accident data is normative for research and policy making, there has been much less statistical modeling work in the U.S. railroad sector. While most existing railroad safety studies have concentrated on derailments or grade crossing collisions, very limited statistical research has been spent on train collision risk analysis. This paper intends to develop an implementable statistical methodology for estimating freight-train collision frequency and severity. One of the most important lessons learned by transportation safety analysts in the past decades is a statistical phenomenon called "Regression to the Mean"

(RTM). The RTM refers to the tendency that a random variable that deviates from the mean will return to "normal" given nothing has changed [19]. In the context of rail safety, it implies that a high accident rate in one year may be followed by a low rate in the next year due to the random fluctuation, even if there is no actual safety change [12]. As Liu (2015) mathematically proves, the RTM is inherent in any empirical train accident data and must be addressed through statistical approaches in order to understand the “true” safety trend [12]. The collision analysis presented in this paper provides a step-by-step procedure to identify the data-driven safety performance function (SPF) in the railroad industry, accounting for random fluctuation in accident occurrence and severity. The general approaches and procedures herein can be adapted to other types of train accidents and severities.

Contributions to the Practice

Risk management is an important activity in the rail industry. However, there is no definitive, normative, practical methodological framework to guide the process of risk assessment. By contrast, the Federal Highway Safety Administration (FHWA) publishes an extensive manual to guide the conduct of statistical modeling of vehicle crash data, based on decades of research [28]. The highway safety manual (HSM) provides practitioners with easy-to-understand tutorials to understand the basic concepts of transportation statistics and toolboxes to statistically analyze and interpret accident data. The author hopes to use this paper, in conjunction with its sequent studies, to promote industry-academic-wide dialogues in order to develop a railroad safety analysis manual, just as the highway sector has done over the past decade. One primary application of statistical modeling of safety data is to evaluate potential collision avoidance technologies. By calculating the accident prediction models before and after implementation of certain risk reduction strategies, decision makers can better understand how a specific technology changes the safety trend, as well as the magnitude of its safety benefit. Ultimately, the railroad research community could develop a data-driven guideline for optimal safety investment.

CONCLUSION

This paper develops a statistical methodology for analyzing freight-train collisions in the United States, based on the data from 2000 to 2014. Using two common mainline collision causes as an example, the analysis shows that the statistical model fits well to the empirical safety data. The statistical model can be used to project freight-train collision risk in the future, enabling a data-driven assessment of the safety effectiveness of certain accident prevention strategies.

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This article is largely based on a more comprehensive study that is described in Liu (2016). The statistical details of train collision risk analysis can be found there [29].

REFERENCES

[1] Federal Railroad Administration (FRA), 2010, National Rail Plan Progress Report, FRA, U.S. Department of Transportation, Washington D.C.

[2] Barkan, C.P.L., Dick, C.T., Anderson, R., 2003, “Railroad Derailment Factors Affecting Hazardous Materials Transportation Risk,” Transportation Research Record, 1825, pp. 64–74.

[3] Anderson, R.T., Barkan, C.P.L., 2004, “Railroad Accident Rates for Use in Transportation Risk Analysis,” Transportation Research Record, 1863, pp. 88–98.

[4] Bagheri, M., Saccomanno, F.F., Chenouri, S., Fu, L.P., 2011, “Reducing the Threat of In Transit Derailments involving Dangerous Goods through Effective Placement along the Train Consist,” Accident Analysis and Prevention, 43(3), pp. 613–620.

[5] Liu, X., Barkan, C.P.L., Saat, M.R., 2011, “Analysis of Derailments by Accident Cause: Evaluating Railroad Track Upgrades to Reduce Transportation Risk,” Transportation Research Record, 2261, pp. 178–185.

[6] Liu, X., Saat, M.R., Barkan, C.P.L., 2012, “Analysis of Causes of Major Train Derailment and Their Effect on Accident Rates,” Transportation Research Record, 2289, pp. 154–163.

[7] Liu, X., Saat, M.R., Barkan, C.P.L., 2013a, “Integrated Risk Reduction Framework to Improve Railway Hazardous Materials Transportation Safety,” Journal of Hazardous Materials, 260, pp. 131–140.

[8] Liu, X., Saat, M.R., Barkan, C.P.L., 2013b, “Safety Effectiveness of Integrated Risk Reduction Strategies for Rail Transport of Hazardous Materials,” Transportation Research Record, 2374, pp. 102–110.

[9] Liu, X., Saat, M.R., Qin, X., Barkan, C.P.L., 2013c, “Analysis of U.S. Freight-train Derailment Severity Using Zero-truncated Negative Binomial Regression and Quantile Regression,” Accident Analysis and Prevention, 59, pp. 87–93.

[10] Liu, X., Saat, M.R., Barkan, C.P.L., 2014a, “Probability Analysis of Multiple-tank-car Release Incidents in Railway Hazardous Materials Transportation,” Journal of Hazardous Materials, 276, pp. 442–451.

[11] Liu, X., Lovett, A., Dick, C.T., Saat, M.R., Barkan, C.P.L., 2014b, “Optimization of Rail Defect Inspection Frequency for the Improvement of Railway Transportation Safety and Efficiency,” Journal of Transportation Engineering, 140 (10).

[12] Liu, X., 2015, “Statistical Temporal Analysis of Freight-train Derailment Rates in the United States: 2000 to 2012,” Transportation Research Record, 2476, pp. 119-125.

[13] Austin, R.D., Carson, J.L., 2002, "An Alternative Accident Prediction Model for Highway-rail Interfaces," Accident Analysis and Prevention, 34 (1), pp. 31–42.
[14] Saccomanno, F.F., Park, P.Y.-J., Fu, L., 2007, "Estimating Countermeasure Effects for Reducing Collisions at Highway-railway Grade Crossings," Accident Analysis and Prevention, 39, pp. 406–416.
[15] Chadwick, S.G., Saat, M.R., Barkan, C.P.L., 2012, "Analysis of Factors Affecting Train Derailments at Highway-rail Grade Crossings," Proceedings of the Transportation Research Board 91st Annual Meeting.
[16] Federal Railroad Administration (FRA), 2011, Guideline for accident report preparation, FRA, U.S. Department of Transportation, Washington D.C.
[17] Nayak, P.R., Rosenfield, D.B., Hagopian, J.H., 1983, Event probabilities and impact zones for hazardous materials accidents on railroads. Report DOT/FRA/ORD-83/20, FRA, U.S. Department of Transportation, Washington D.C.
[18] Association of American Railroads (AAR), 2013, Class I railroad statistics.
[19] Hauer, E., 1997, *Observational Before-After Studies in Road Safety*, Pergamon Press, Elsevier Science Ltd., Oxford, England.
[20] Kaplan, S., Garrick, B.J., 1981, "On the Quantitative Definition of Risk," Risk Analysis, 1(1), pp. 11-27.
[21] Arthur D. Little, Inc. (ADL), 1996, "Risk Assessment for the Transportation of Hazardous Materials by Rail," Supplementary Report: Railroad Accident Rate and Risk Reduction Option Effectiveness Analysis and Data, second revision, Cambridge, Mass.
[22] Evans, A.W., 2007, "Rail Safety and Rail Privatization in Great Britain," Accident Analysis and Prevention, 39(3), pp. 510-523.
[23] Evans, A.W., 2010, "Rail Safety and Rail Privatization in Japan," Accident Analysis and Prevention, 42(4), pp. 1296-1310.
[24] Evans, A.W., 2011, "Fatal Train Accidents on Europe's Railways: 1980-2009," Accident Analysis and Prevention, 43(1), pp. 391-401.
[25] Hilbe, J.M., 2007, *Negative binomial regression*, Cambridge University Press.
[26] Bradley, 1968, *Distribution-Free Statistical Tests*, Prentice-Hall.
[27] Goodman, L.A., 1962, "The Variance of the Product of K Random Variables," Journal of the American Statistical Association.
[28] American Association of State Highway and Transportation Officials (AASHTO), 2015, "An introduction to highway safety manual," http://www.highwaysafetymanual.org/Documents/HSMP-1.pdf.
[29] Liu, X., 2016, "Collision risk analysis of freight trains in the United States," Annual Meeting of the Transportation Research Board, Washington D.C.