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Freight-train derailment rates for railroad safety and risk analysis

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ABSTRACT

Derailments are the most common type of train accident in the United States. They cause damage to infrastructure, rolling stock and lading, disrupt service, and have the potential to cause casualties, and harm the environment. Train safety and risk analysis relies on accurate assessment of derailment likelihood. Derailment rate – the number of derailments normalized by traffic exposure – is a useful statistic to estimate the likelihood of a derailment. Despite its importance, derailment rate analysis using multiple factors has not been previously developed. In this paper, we present an analysis of derailment rates on Class I railroad mainlines based on data from the U.S. Federal Railroad Administration and the major freight railroads. The point estimator and confidence interval of train and car derailment rates are developed by FRA track class, method of operation and annual traffic density. The analysis shows that signaled track with higher FRA track class and higher traffic density is associated with a lower derailment rate. The new accident rates have important implications for safety and risk management decisions, such as the routing of hazardous materials.

1. Introduction

Derailments are the most common type of train accident in the United States. They cause damage to infrastructure, rolling stock and lading, disrupt service, and have the potential to cause casualties and harm the environment. Understanding the most important factors affecting derailments is critical to development of effective risk reduction strategies. Train safety and risk analysis relies on accurate estimation of derailment rate, which is defined as the number of derailments normalized by some metric of traffic exposure, such as train-miles, car-miles or gross ton-miles (Nayak et al., 1983; Treichel and Barkan, 1993; Anderson and Barkan, 2004; Liu et al., 2011).

Highway safety researchers have conducted a number of studies quantifying the relationship between accident rates and roadway design. These studies have considered the effects of road curvature, traffic volume, grade, shoulder width, number of lanes and other factors (e.g., Miaou, 1994; Maher and Summersgill, 1996; Hauer, 2001; Lord et al., 2005; Lord, 2006; Mitra and Washington, 2007). The earliest example of a comprehensive analogous study of railroad accident rates in the United States was conducted by Nayak et al. in the 1980s (Nayak et al., 1983). Using analyses of accident frequency and rail traffic volume, they found a strong statistical correlation between FRA track class and derailment rate. A subsequent unpublished study by Treichel and Barkan (1993) found a similar result and Anderson and Barkan (2004) used new data to develop updated estimates. All of these studies found that higher FRA track classes had lower derailment rates, varying by more than an order of magnitude. This relationship was not surprising; higher FRA track classes are intended to ensure safe operation at higher operating speeds and therefore require a variety of more stringent engineering safety and maintenance standards (FRA, 2011a).

Nayak et al's (1983) estimates, and the updates cited above, have been used by railroads, chemical companies, government agencies, researchers and others to address a variety of risk analysis and management questions (Glickman and Rosenfield, 1984; Rhyne, 1994; CCPS, 1995; ADL, 1996; STB, 2003; Kawprasert and Barkan, 2008, 2010). However, as the importance and sophistication of these questions has grown, so too has the importance of their accuracy. Simple predictive models of derailment rate based solely on a sin-

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gle parameter, FRA track class, might not satisfactorily account for all the pertinent factors. This led to closer scrutiny of other possible factors that might affect the relationship between FRA track class and derailment rate. Developing a better understanding of such relationships is important for improved railroad risk management practices.

Since 1980 the U.S. railroad derailment rate has declined from 8.98 derailments per million train miles, to 1.63 in 2014, an 82% reduction (FRA, 1980, 2015). These derailment rates reflect statistics for all FRA track classes combined; however, they do not permit evaluation of the relative rate on different track classes, nor the possible effect of other factors. The relative importance of accident causes correlated with different track classes may co-vary with other factors and may shift as a result of changes in various factors (Anderson and Barkan, 2004). There is ongoing interest in improving rail safety and new concerns have been raised regarding the risk of rail transport of hazardous materials due to several fatal release accidents involving toxic inhalation hazard (TIH) materials in the mid-2000s, and more recent accidents resulting in large releases of flammable liquids. This prompted renewed interest in a more detailed understanding of the factors affecting derailment rate (Liu et al., 2012; Liu, 2015). In the same time frame, post-9/11 security concerns led the US Department of Transportation to promulgate new regulations that required railroads to conduct, "transportation route analysis, alternative route analysis, and route selection" for TIH materials (DOT, 2008). This led to new consideration of how to calculate derailment rate and whether it provided a sufficiently detailed means of assessing localized risk. Research by the authors of this paper suggested that other factors not previously considered might be affecting it as well, notably method of operation (i.e. traffic control system) and traffic density.

Previous constraints on data systems and availability had limited the ability to consider more fine-grained questions regarding factors that might co-vary with track class and affect derailment rate. Furthermore, these analyses had used relatively simple statistical techniques that were not capable of detecting the complex relationship between derailment rates and multiple influencing factors. To address these questions, a new dataset was developed that contained information on FRA track class, method of operation and traffic density.

2. Data and variables

2.1. Derailment and traffic data

Data for the derailment rate analysis were obtained for the major freight railroads operating in the U.S. for the years 2005 to 2009. These railroads account for approximately 69% of route miles and 88% of carloads transported on U.S. railroads (AAR, 2013). The analysis in this paper focuses on train derailments, and excludes other types of train accidents, such as collisions or highway-rail grade crossing incidents.

Data on the number and cause of derailments came from the U.S. Federal Railroad Administration (FRA) Rail Equipment Accident (REA) database (FRA, 2015). This database records all accidents that exceed a specified monetary damage cost to on-track equipment, signals, track, track structures, and roadbed (FRA, 2011a). Each accident record includes information on approximately 50 different variables detailing the circumstances of the accident. Among these are the FRA track class, method of operation and the annual traffic density measured in annual gross tonnage at the accident location. However, having traffic density data for FRA-reportable accident locations only is insufficient for proper estimation of derailment rates because it does not permit understanding of the entire network under consideration. In particular, comprehensive data on the exposure of rail traffic to different combinations of infrastructure and operating conditions are needed to develop accurate estimates of accident rates. Therefore, each railroad provided additional data for their entire, mainline network. In total, there were 1420 freight-train derailments and 17.5 trillion gross ton-miles of traffic (corresponding to more than 2.5 billion train miles) reported for the mainline network in the 2005–2009 time period covered in this analysis.

As discussed above, the train safety and traffic data came from different sources; the former came from the FRA (2015) and the latter from major freight railroads. Although the various datasets contained all of the necessary information and variables needed, their structure and organization differed in terms of segment-specific information. Furthermore, they did not contain consistent geographical information system (GIS) information. Assembling and integrating these databases required considerable effort and care. The lack of consistent geo-coding constrained our ability to reliably relate the location of each derailment to the exact network location for which we had traffic data. This limited our ability to conduct a segment-specific train derailment rate analysis in the manner commonly used in highway accident rate analysis (Miaou, 1994; Maher and Summersgill, 1996; Miaou and Lord, 2003) so we developed an alternative approach.

As discussed above the FRA (2015) database records all the parameters of interest in the study and the railroad databases provided reliable system-wide traffic information for the same parameters. Consequently, we approached the problem as a cross-classified categorical modeling problem using aggregated data classified by the predictor variables of interest (Fienberg, 1980; Agresti, 2007). We then conducted a regression analysis based on the total number of derailments and the corresponding traffic exposure for each combination of predictor variables. A detailed explanation of the methodology is presented in Section 3.

2.2. Explanatory variables

The selection of the following variables and their categorization was based on insights from previous research and questions posed by rail industry experts. Furthermore, the three predictor variables are among the risk factors that the US DOT Pipeline and Hazardous Materials Safety Administration (PHMSA) requires railroads to consider in their hazardous materials transportation risk management process (PHMSA, 2008).

2.2.1. FRA track class

The FRA specifies track quality standards or "track classes" for operation of freight and passenger trains at different maximum allowable operating speeds (FRA, 2011a). There are five principal track classes commonly used by U.S. freight railroads, ranging from class 1 with the lowest maximum allowable freight-train speed (10 mph), to class 5 with the highest (80 mph). These classes include specifications for track structure, geometry, inspection frequency and method of inspection, with more stringent requirements for higher track classes. The FRA standards represent minimum requirements; in fact, railroads often maintain various sections of their infrastructure to standards that exceed the minimum required by the FRA. This introduces additional variance in statistical analyses of the relationship between track quality and derailment rates within the same track class (El-Sibaie and Zhang, 2004).

2.2.2. Method of operation

When this study was conducted, the FRA recorded 12 different values for method of operation. For the purposes of our analysis, we were interested in a higher level categorization, specifically, whether the track had a system of automatic signaling in place or not (i.e. "signaled" versus "non-signaled" territory, respectively) so we collapsed the 12 categories to one of these two conditions. Since then, FRA (2011b) has simplified their system so it only records these two categories as well. This categorization was also identified as one of the risk factors specified by the Pipeline and Hazardous Materials Safety Administration (PHMSA) for railroad hazardous materials route analysis and selection (PHMSA, 2008). Approximately 60 percent of U.S. mileage and 80 percent of rail traffic operates on signaled trackage (FRA, 2008). Such trackage uses low-voltage, electric current in the rails (known as "track circuits") to detect the presence of trains in a given section. An important secondary benefit of track circuits is that they enable detection of several types of infrastructure problems, most notably in the context of this study, are broken rails, which are the leading cause of major derailments on U.S. railroad mainlines (Dick et al., 2003; Barkan et al., 2003; Liu et al., 2012).

2.2.3. Traffic density

Traffic density was the third variable included in the model. Track with a higher traffic density receives more frequent track maintenance leading to higher track quality (FRA, 2011a; Peng, 2011). Railroad traffic density represents the total weight of all locomotives, rolling stock and lading traversing a given section of track and is commonly measured in million gross tons (MGT). The traffic density variable was assigned two values, <20 MGT annual traffic and ≥20 MGT. The demarcation at 20 MGT was selected because it represents the average annual track traffic density on all U.S. Class I railroad mainlines (2005-2009) so the two classifications indicate, below average traffic density and above average, respectively. This level is also the threshold used by the Association of American Railroads as their criterion for high-density track (AAR, 2016). We considered a finer grained approach to this parameter but were constrained by the fact that railroads' traffic density reporting practices vary. Some railroads provided traffic data for each individual track, while others could only provide total traffic density for all tracks on the same corridor. This limited our ability to reliably conduct a finer grained classification of the traffic on each track hence we used a simple, binary classification for this parameter.

As mentioned above, FRA track class is determined by speed of operation. Maximum allowable speed along a route will fluctuate because of civil speed restrictions that are due to curvature, infrastructure features and various other permanent operating restrictions. Railroads indicate allowable speed for each segment of track in their operating timetables and FRA uses these timetable speeds as the basis for track class and the corresponding regulatory requirements for track safety (FRA, 2011a). Segments with lower allowable speed will generally be classified as lower FRA track classes. However, on high-traffic-density routes these lower-speed sections are generally designed and maintained to the same high standards as adjacent sections on the route with higher speeds and track classes, commensurate with the higher volume of traffic using them.

Having assembled the data from the various sources and ensuring its consistency with regard to the predictor variables of interest, we prepared two $5 \times 2 \times 2$ matrices for the rail network and time period studied, one for derailments, and the other for traffic. These matrices were classified according to each combination of FRA track class, method of operation and traffic density as follows:

- FRA Track Class: 1, 2, 3, 4, 5;
- Method of Operation: signaled and non-signaled;
- Annual Traffic Density: <20 MGT and ≥20 MGT.

Table 1 presents the distribution of freight-train derailment and traffic data by the predictor factors used in our study. Approximately 54 percent of the derailments and 85 percent of traffic exposure are on higher FRA track classes (class 3 to class 5), signaled track with annual traffic density above 20 MGT. This concentration of traffic reflects industry practice to maximize operational efficiency. Lines with higher traffic are designed and maintained to achieve greater speed, safety and capacity. Therefore, most of the cells in the matrix are based on other, lower speed and density conditions. In our study, we considered all possible combinations of predictor variables, with each categorical predictor variable appearing equally (once). This approach was used to avoid collinearity problems between predictor variables.

Note that traffic volume (ton-miles) is an exposure variable distinct from the predictor variable used in our model. In the next section we describe the negative binomial regression model that was developed to analyze mainline freight-train derailment rate.

3. Analysis

3.1. Train derailment rate

This paper uses negative binomial (NB) regression model to analyze freight-train derailment rates on U.S. Class I railroad main tracks. The NB model has been widely used in accident rate analysis in highway transportation (e.g., Miaou, 1994; Hauer, 2001; Wood, 2002; Lord et al., 2005; Lord, 2006; Oh et al., 2006; Mitra and Washington, 2007) and its basic framework is as follows:

$$Y \sim Poisson(\lambda) \tag{1}$$

$$\lambda \sim Gamma(f, \frac{f}{m}) \tag{2}$$

$$m = \exp\left(\sum_{p=0}^{k} b_P X_P\right) M \tag{3}$$

Where:

Y = observed number of derailments
m = estimated number of derailments
b_p = p^{th} parameter coefficient
X_p = p^{th} explanatory variable
M = traffic exposure (gross ton-miles)
f = inverse dispersion parameter

The confidence intervals of estimated derailment rates using the Poisson regression or negative binomial regression models are developed by Wood (2005) (Table 2).

$$Z = \exp(b_0 + b_{trk}X_{trk} + b_{moo}X_{moo} + b_{den}X_{den}) \tag{4}$$

Where:

Z = estimated derailment rate per gross ton-miles
X_{trk} = FRA track class (1 to 5)
X_{moo} = method of operation (1 for signaled, 0 for non-signaled)
X_{den} = annual traffic density level (1 for ≥ 20 MGT, 0 for < 20 MGT)
b = parameter coefficients

All mainline derailment locations in the network were included and categorized in our dataset. Similarly, traffic data for the entire network were included, regardless of whether an accident occurred at a particular location. Thus, the traffic data are a comprehensive representation of the mainline operating and infrastructure conditions that rail traffic was exposed to during the study period. In contrast to highway safety analysis, which is typically based on short, uniform-length road sections using public data, the railroad accident data available required us to use a different method to satisfactorily resolve constraints in the data structure regarding its granularity and consistency, especially considering that the data came from different sources.

Table 1
Distribution of (a) derailment and (b) traffic data by predictor variables.

Annual Traffic Density (MGT)	Method of Operation (MO)	FRA Track Class (TC)					
		1	2	3	4	5	TC Total
(a)							
<20	Non-Signaled	2.00%	3.50%	4.40%	3.70%	n/a[a]	13.70%
	Signaled	1.30%	2.50%	3.30%	4.60%	0.40%	12.20%
	MO Total	3.40%	6.10%	7.70%	8.30%	0.40%	25.80%
≥20	Non-Signaled	0.70%	1.80%	2.00%	6.00%	0.50%	11.00%
	Signaled	2.60%	6.70%	11.30%	31.00%	11.60%	63.20%
	MO Total	3.30%	8.50%	13.20%	37.00%	12.10%	74.20%
Total	Non-Signaled	2.70%	5.40%	6.30%	9.70%	0.50%	24.60%
	Signaled	3.90%	9.20%	14.60%	35.60%	12.00%	75.40%
	MO Total	6.70%	14.60%	20.90%	45.30%	12.50%	100.00%
(b)							
<20	Non-Signaled	0.10%	0.50%	0.90%	1.60%	*n/a	3.20%
	Signaled	0.10%	0.30%	1.20%	3.30%	0.30%	5.20%
	MO Total	0.20%	0.90%	2.10%	4.90%	0.30%	8.40%
≥20	Non-Signaled	0.20%	0.40%	0.80%	2.10%	0.20%	3.70%
	Signaled	0.50%	2.00%	8.20%	47.80%	29.40%	88.00%
	MO Total	0.70%	2.40%	9.00%	49.90%	29.70%	91.60%
Total	Non-Signaled	0.30%	0.90%	1.70%	3.70%	0.20%	6.90%
	Signaled	0.50%	2.40%	9.40%	51.10%	29.70%	93.10%
	MO Total	0.80%	3.30%	11.10%	54.70%	30.00%	100.00%

[a] There were no instances of non-signaled, Class 5 track with less than 20 MGT of annual traffic.

Table 2
95% confidence interval for train derailment rate estimate (Wood, 2005).

Poisson	
m	$\exp[X^T b^* \pm 1.96\sqrt{Var(h^*)}]$
y	$\left[0, \lfloor m^* + \sqrt{19}\sqrt{(m^*)^2 Var(h^*) + m^*}\rfloor\right]$
Negative binomial	
m	$\exp[X^T b^* \pm 1.96\sqrt{Var(h^*)}]$
λ	$\max\left\{0, m^* - 1.96\sqrt{(m^*)^2 Var(h^*) + \frac{(m^*)^2 Var(h^*)+(m^*)^2}{f^*}}\right\}, m^* + 1.96\sqrt{(m^*)^2 Var(h^*) + \frac{(m^*)^2 Var(h^*)+(m^*)^2}{f^*}}\Bigg\}$
y	$\left[0, \lfloor m^* + \sqrt{19}\sqrt{(m^*)^2 Var(h^*) + \frac{(m^*)^2 Var(h^*)+(m^*)^2}{f^*} + m^*}\rfloor\right]$

Note: $h^* = b_0{}^* + b_1{}^* X_1 + \ldots + b_k{}^* X_k + \log(M)$(the parameter with * represents an estimator)

We developed an aggregation-based approach that classifies the total number of train accidents and total traffic exposure (including locations with zero accidents) into several categories by the combination of the three predictor variables. In the aggregation-based analysis, the total derailment count in each category is a sufficient statistic for estimating the unknown parameters, which means no information is lost by aggregating Poisson-based accident count. Put another way, the "effective sample size" in the aggregated model is related to the aggregated counts and the total traffic exposure, instead of the number of categories. Similar applications of the aggregated approach in log-linear modeling can be found in the literature (e.g., Abdel-Aty and Abdelwahab, 2000; Agresti, 2007). The theoretical rationale and limitations of this aggregation method are presented in Appendix A.

The estimated parameter coefficients were developed using the maximum likelihood method (Agresti, 2007) and all three variables were found to significantly affect freight-train derailment rates (Table 3). The model diagnostics were evaluated and found to be adequate using a statistical criterion called Deviance (P-value = 0.01). Although FRA track class is an ordinal categorical variable, the preliminary data analysis suggested that there was an inverse linear relationship between logarithmic derailment rate and FRA track class (parameter coefficient for track class 1 is 2.486; for track class 2 is 1.998; for track class 3 is 1.269; for track class 4 is 0.498; for class 5 is 0 by setting class 5 as the reference class), given the other two predictor variables. This indicates that train derailment rate has an exponential relationship with FRA track class if treated as a continuous variable. A similar relationship has been found by other researchers using earlier data (Nayak et al., 1983; Anderson and Barkan 2004; English et al., 2007)

A special case of the negative binomial model is the Poisson model with a dispersion parameter of zero (Hilbe, 2007). To test whether this was appropriate for our data, we calculated the Wald z-score by dividing the estimated dispersion parameter by its standard error. The calculated z-score was 0.77 (0.0048/0.0062), which fails to reject the hypothesis of a zero dispersion parameter (p = 0.44). This indicated that there is no significant difference between the Poisson model and negative binomial model in fitting the data. Thus we used the confidence intervals for the Poisson model (Table 2) to estimate the 95% confidence intervals for train derailment rates (Fig. 1 and Table 4). It is evident that all three variables are having a substantial effect:

1) The higher the FRA track class, the lower the train derailment rate.
2) Signaled track has a lower derailment rate than non-signaled track.
3) Track with higher traffic density has a lower derailment rate.

Table 3
Parameter coefficient estimates of freight-train derailment rate per billion gross ton-miles on Class I mainlines, from 2005 to 2009.

Parameter	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
b_0 (Intercept)	0.9201	0.1115	0.7016	1.1386	68.11	<0.0001
b_{trk} (Track Class)	−0.6649	0.0341	−0.7318	−0.5981	380.37	<0.0001
b_{moo} (Method of Operation)	−0.3377	0.0974	−0.5286	−0.1469	12.03	0.0005
b_{den} (Annual Traffic Density)	−0.7524	0.0859	−0.9208	−0.5840	76.72	<0.0001
Dispersion	0.0048	0.0062				

Notes: 1) Over the five-year period covered in this study there were a total of 1420 derailments and 17.5 trillion gross ton-miles of freight train traffic assigned to the 20 different categories in the cross-categorical matrix used in the statistical analysis (one cell in the matrix: <20 MGT, Non-Signaled, Class 5 Track had no accidents or traffic resulting in a total of 19 cells used to conduct the analysis). 2) Traffic exposure is measured by gross ton-miles, and annual traffic density is measured by gross tonnage on a segment.

Table 4
Estimated Class I mainline freight-train derailment rate per billion gross ton-miles, 2005–2009 (the numbers in the parenthesis represent 95% confidence intervals).

Annual Traffic Density (MGT)	Method of Operation	FRA Track Class				
		Class 1	Class 2	Class 3	Class 4	Class 5
<20	Non-Signaled	1.29 (1.086, 1.534)	0.66 (0.574, 0.768)	0.34 (0.295, 0.395)	0.18 (0.148, 0.209)	n/a[a]
	Signaled	0.92 (0.737, 1.151)	0.47 (0.395, 0.568)	0.24 (0.208, 0.286)	0.13 (0.106, 0.147)	0.06 (0.053, 0.078)
≥20	Non-Signaled	0.61 (0.495, 0.747)	0.31 (0.260, 0.376)	0.16 (0.134, 0.194)	0.08 (0.067,0.102)	0.04 (0.033, 0.055)
	Signaled	0.43 (0.361, 0.521)	0.22 (0.195, 0.255)	0.11 (0.104, 0.127)	0.06 (0.053, 0.066)	0.03 (0.026, 0.035)

[a] There were no instances of non-signaled, Class 5 track with less than 20 MGT of annual traffic.

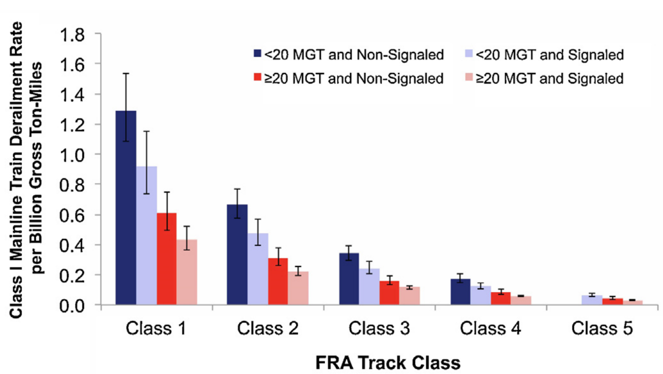

Fig. 1. Estimated Class I mainline freight-train derailment rates by FRA track class, method of operation and annual traffic density (error bars indicate 95% confidence intervals).

The observation that a higher track class is associated with a lower train derailment rate is consistent with previous studies (Nayak et al., 1983; Treichel and Barkan, 1993; Anderson and Barkan, 2004). However, in addition to FRA track class, method of operation and traffic density both had a strong, significant relationship with derailment rate. As mentioned above, signaled track segments have track circuits to detect broken rails, thereby potentially reducing the likelihood of derailments due to this cause. Furthermore, given the same track class and method of operation, derailment rate is inversely related to traffic density level. There are several possible explanations for this. As mentioned above rail lines with higher traffic density receive more frequent track inspection and maintenance (Zarembski and Palese, 2010; Sawadisavi, 2010; Peng, 2011) irrespective of speed (i.e. FRA track class). Busier lines may also have a greater number and variety of wayside defect detectors installed (Schlake, 2010) thereby reducing the incidence of certain infrastructure and equipment-caused train accidents.

3.2. Railcar derailment rate

3.2.1. Calculation of railcar derailment rate

In addition to train derailment rate, railcar derailment rate is also of interest. This is generally measured as the number of cars derailed per unit of traffic exposure and represents the likelihood that an individual railcar is involved in a derailment. Anderson and Barkan (2004) estimated average car derailment rate by multiplying train derailment rate by the average number of cars derailed per derailment:

$$C^* = \frac{m^* \times D^*}{M} \quad (5)$$

Where:
C^* = estimated car derailment rate per unit of traffic exposure
m^* = estimated train derailment count given traffic exposure
D^* = average number of cars derailed per train derailment (severity)
M = traffic exposure

3.2.2. Derailment severity

The average number of cars derailed in derailment is a metric of its severity (Nayak et al., 1983; Saccomanno and El-Hage, 1989; Barkan et al., 2003; Anderson and Barkan, 2004; Liu et al., 2013a,b) and can be calculated using data from the same FRA REA database used to address other questions in this paper. We conducted an analysis of variance (ANOVA) to determine if there was a relationship between derailment severity and the three explanatory variables being considered. We found no significant relationship with Method of Operation (F statistic = 1.21, degrees of freedom = 1, P = 0.27) or traffic density (F statistic = 0.57, degrees of freedom = 1, P = 0.6). However, we did find a significant relationship between FRA track class and derailment severity (F statistic = 4.78, degrees of freedom = 4, P < 0.01). The higher the FRA track class, the greater the average number of cars derailed per train derailment.

The lack of a relationship between severity and the first two variables is not surprising because, *ceteris paribus*, neither would be expected to affect the kinetic energy of a derailment and consequently its severity, whereas the third one does. Track class is directly related to maximum allowable operating speed and previous research has shown a relationship between severity and derailment speed, due in part to the greater kinetic energy (Nayak et al., 1983; Barkan et al., 2003; Anderson and Barkan, 2004) and with FRA track class (Liu et al., 2011). Thus, track-class-specific number of cars derailed was estimated and used to estimate car derailment rate.

3.2.3. Variance in estimated railcar derailment rate

We also calculated the variance in the car derailment rate estimate by accounting for the uncertainty in train derailment rate and number of cars derailed. A general approach to estimate the variance of multiple random variables was originally developed in the 1960s (Goodman, 1962). Since then, it has been used in studies of highway safety (Lord, 2008; Geedipally and Lord, 2010) but we are unaware of its application to estimation of railcar derailment rate. Train derailment frequency and severity were assumed to be independent variables, and the variance in estimated car derailment rate, denoted by Var(C^*), was estimated using the following equation (derived in Appendix B):

$$Var(C^*) = \frac{[E(m^*)]^2 Var(D^*) + [E(D^*)]^2 Var(m^*) + Var(m^*)Var(D^*)}{M^2} \quad (6)$$

where:
Var(C^*) = variance of estimated car derailment rate
E(m^*) = expected value of train derailment count
Var(m^*) = variance of estimated train derailment count
E(D^*) = expected value of number of cars derailed per derailment
Var(D^*) = variance of estimated number of cars derailed per derailment
M = traffic exposure

4. Implications of the Results

Multivariate statistical analyses of North American train derailment data, combined with information on FRA track class, method of operation and traffic density, showed that each of these variables had a strong, significant effect on derailment rate. Previous studies had only found an effect of track class, but did not consider the other two variables. We also found that average derailment severity was unaffected by method of operation or traffic density, but was strongly related to FRA track class, consistent with several previous studies (Nayak et al., 1983; Barkan et al., 2003; Anderson and Barkan, 2004). Despite the higher average number of cars derailed in accidents on higher track classes, car derailment rate is still lower. This is because the reduction of train derailment rate more than offsets the increase in derailment severity.

Accurate calculation of train accident rate has important implications for a number of railroad industry safety policy, operating practice, risk management and resource allocation decisions. It is also an important aspect of federal regulatory development, review policies and decision making. The first attempt to develop nationwide, track-class-specific accident rates was conducted by Nayak et al. (1983) in a study conducted for the US DOT Federal Railroad Administration. Railroad train safety had been deteriorating in the years prior to economic deregulation of the US rail industry in 1980 and there was interest in understanding the effect of various potential contributing factors. Meanwhile, in 1975 the FRA had implemented new train accident data recording requirements and Nayak et al. used these data, along with data from other sources, to try and understand the quantitative relationship between track class and derailment rate.

At the same time, there was increasing interest in the risk associated with rail transport of hazardous materials such as toxic-inhalation-hazard materials and flammable gases (Andrews, 1980; Geffen, 1980). In the absence of more specific data, these studies relied on an average railroad derailment rate. Although such an approach may enable nationwide estimates of average risk, most rail transport risk management decisions require greater precision. For example understanding localized differences in risk due to differing track quality or development of risk profiles for a route or region. Nayak et al. recognized that both national, and geographically specific estimates of train safety and derailment risk required finer grained understanding of the key factors affecting risk. Since that time, both the private and public sectors have made extensive use of the FRA database, the Nayak et al. statistics, and subsequent revisions and refinements of their analyses using track-class-specific derailment rates to conduct safety and risk assessments at both the local and national level (Glickman and Rosenfield, 1984; CCPS, 1995; STB, 2003; Kawprasert and Barkan, 2010).

Part of the track-class effect observed in previous studies was likely due to co-variance with the other two variables described in this paper, but even when that is accounted for, FRA track class still has a strong effect. The results presented in this paper indicate that track class is one of (at least) three different factors that are significantly related to derailment rate. This new, three-factor derailment rate model provides better resolution for estimating mainline derailment rates on U.S. railroads and has implications for rail safety policy and practice compared to use of the earlier single-factor, track-class-specific model.

5. Discussion

The current variable categorization and data matrix structure is constrained by the format of the data that railroads record and were able to provide. For example, the five FRA track classes are specified by their Track Safety Standards (FRA, 2011a). Dark territory (non-signaled) and signalization represent the two basic types of method of operation. The annual traffic density demarcation (i.e., 20 MGT in this study) represents the average level of traffic on Class 1 railroad mainlines and is designated by AAR (2016) as the threshold for "High-Density Track". As discussed above finer-grained differentiation of the data categories, especially traffic density, would have enabled a more robust statistical analysis and greater resolution in the results. However, because the different railroads have different definitions and procedures for recording their data, we were constrained in the level of resolution that we had confidence in, hence the 20 MGT demarcation, which we do believe is reliable. The three categorical variables used, and categories within each, are institutionally constrained to conform to the U.S. railroad industry and government practice, which in turn defines the nature of the data provided by the railroads.

As a consequence of the data grouping there was considerable heterogeneity in the distribution of the traffic in the $2 \times 2 \times 5$ matrix developed for the analysis. In particular, just three cells, FRA track classes 4 and 5, with signals and greater than 20 MGT traffic density, accounted for approximately 77 percent of the traffic exposure. This is because lines with higher traffic are designed and maintained to achieve greater speed, safety and capacity. All of these co-vary with the parameters of the three matrix cells referenced above so it is not surprising that the bulk of the traffic was on portions of the network with these conditions. As a result, most of the data points in the matrix are based on the other, lower density conditions, thereby introducing some additional uncertainly in the regression results.

We are hopeful that this paper will lead to further research in which some of this uncertainty can be resolved through more refined recording of data. Ideally, this would involve segment-specific traffic exposure and derailment data from each railroad, using a consistent data format and organizational structure. In particular, we hope to have a more detailed data for traffic density.

This would allow delineation of key predictor variables into finer levels, and development of more balanced derailment and traffic distributions for statistical analysis.

6. Conclusion

This paper describes an analysis of train and railcar derailment rates on Class I railroad mainline tracks in the United States. FRA track class has been the principal factor used previously to quantitatively assess, location-specific derailment rate in rail transportation safety and risk studies for over three decades. The analysis described here accounts for two new factors (method of operation and annual traffic density) that were also found to have a strong and significant effect.

The U.S. Class 1 railroads' derailment rate has continued to decline since the data for this study were collected (Liu, 2015) and the derailment rate in 2014 was estimated to be about a third lower than the average rates presented here (Barkan et al., 2015). The methodology described here can be employed to update these statistics when appropriate. The statistical results can be used for more accurate train safety and risk analyses, thereby enabling more precise estimates of local and route-specific risk, and contributing to development of more effective risk reduction strategies to improve rail safety.

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Appendix A.

The rationale of the aggregation-based derailment rate analysis is illustrated using the following example. Assuming there are two track segments with the same: FRA track class (1, 2, 3, 4 or 5), method of operation (non-signaled versus signaled) and annual traffic density level (<20 or ≥20 MGT). On each segment, the number of train derailments (Y_1 and Y_2, respectively) follows a Poisson distribution. The observed accident count is described as a function of the predictor variables:

$$Y_1 = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3) M_1 + \text{error}_1 \tag{A.1}$$

$$Y_2 = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3) M_2 + \text{error}_2 \tag{A.2}$$

Where:

Y_1 = observed number of train derailments on the first segment,

Y_2 = observed number of train derailments on the second segment,

X_1 = FRA track class (1–5),

X_2 = method of operation (1 = signaled, 0 otherwise),

X_3 = annual traffic density (1 = 20 MGT or greater, 0 otherwise),

error_1 = random error of accident count on segment 1,

error_2 = random error of accident count on segment 2.

The sum of independent Poisson distributions also conforms to a Poisson distribution (Agresti, 2007). Therefore, the sum of derailments on the two segments ($Y_1 + Y_2$) also follows a Poisson distribution, that is:

$$Y_1 + Y_2 = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3)(M_1 + M_2) + (\text{error}_1 + \text{error}_2) \tag{A.3}$$

Where, $M_1 + M_2$ is the total traffic exposure on the two segments.

Disaggregated model: Using this method, the two segments are treated as two units of observations. The likelihood function for this model is:

$$L_1 = \frac{\left[\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3) M_1\right]^{Y_1}}{Y_1!} \exp(-\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3) M_1 \times \frac{\left[\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3) M_1\right]^{Y_2}}{Y_2!} \exp(-\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3) M_2 \tag{A.4}$$

Eq. (A.4) is mathematically equivalent to Eq. (A.5):

$$L_1 = \frac{\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3)^{Y_1 + Y_2} {M_1}^{Y_1} {M_2}^{Y_2}}{Y_1! Y_2!} \exp[-\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3)(M_1 + M_2)] \tag{A.5}$$

Aggregated model: In this method, the aggregation of the two segments is treated as one unit of observation. Its likelihood function is:

$$L_2 = \frac{\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3)^{Y_1 + Y_2} (M_1 + M_2)^{Y_1 + Y_2}}{(Y_1 + Y_2)!} \exp(-\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3)(M_1 + M_2)) \tag{A.6}$$

Comparing L_1 & L_2, it is evident that the aggregated and disaggregated models have the same maximum likelihood estimator (MLE) derived from their respective likelihood. Therefore, the aggregation of multiple segments with the same features may not affect the estimation of parameter coefficients under certain conditions. This assumption could be validated with more granular segment-specific safety and traffic data, when such information becomes available.

Appendix B.

Average car derailment rate can be estimated by multiplying train derailment rate by average number of cars derailed per derailment (Anderson and Barkan, 2004).

$$C^* = \frac{m^* \times D^*}{M} \tag{B.1}$$

Where:

C^* = estimated car derailment rate per traffic exposure

m^* = estimated train derailment count given traffic exposure

D^* = average number of cars derailed per train derailment

M = traffic exposure

The variance in estimated car derailment rate is denoted by $Var(C^*)$. Assuming that estimated train derailment count and estimated derailment severity are independent, $Var(C^*)$ is calculated using the model developed by Goodman (1962):

$$Var(C^*) = \frac{[E(m^*)]^2 Var(D^*) + [E(D^*)]^2 Var(m^*) + Var(m^*) Var(D^*)}{M^2} \tag{B.2}$$

Table B1
Average number of cars derailed per freight-train derailment on Class I railroad mainlines, 2005–2009.

	FRA Track Class				
	1	2	3	4	5
Average Number of Cars Derailed per Derailment	5.3	7.3	8.5	9.3	10.0
Standard Error	0.3	0.7	0.9	1.2	1.4
Maximum Operating Speed (mph) of Freight-Trains	10	25	40	60	80

Table B2
Estimated car derailment rate per billion car-miles, Class I freight-train mainline derailments, 2005–2009 (Italic numbers in the parentheses represent the standard error of estimated car derailment rates).

Annual Traffic Density (MGT)	Method of Operation	FRA Track Class				
		1	2	3	4	5
<20	Non-Signaled	632 (66)	446 (55)	266 (35)	150 (23)	n/a[a]
	Signaled	451 (57)	318 (43)	189 (25)	107 (16)	59 (10)
≥20	Non-Signaled	298 (35)	210 (29)	125 (18)	71 (12)	39 (7)
	Signaled	213 (23)	150 (18)	89 (11)	50 (7)	28 (4)

[a] There were no instances of non-signaled, Class 5 track with less than 20 MGT of annual traffic.

The higher the FRA track class, the greater the average number of cars derailed. It is probably due to the greater maximum allowable operating speeds on higher track classes (Table B1). Track-class-specific number of cars derailed per derailment was calculated and used to estimate car derailment rate, measured by number of railcars derailed per billion gross ton-miles.

The traffic volumes provided by railroads are in gross ton-miles (GTM). A railroad-specific conversion factor was developed to project car-mile data, for converting car derailment rate per billion gross ton-miles to car derailment rate per billion car-miles. The conversion factor (91.61) was developed based on the gross ton-miles and car-miles statistics on Class I mainlines (2005-2009). The results of estimated car derailment rate per billion car-miles are presented in Table B2.

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