

Statistical Temporal Analysis of Freight Train Derailment Rates in the United States 2000 to 2012

Xiang Liu

Safety is the top priority for every rail system in the world. A widely used measure for rail safety is the accident rate, which is the number of train accidents normalized by traffic exposure. Of interest in rail safety research is understanding the temporal trend of accident rates, the significant factors affecting the trend, and how to predict accident rates. This paper uses a negative binomial regression model to present a statistical analysis of U.S. Class I railroad freight train derailment rates on main tracks by year and accident cause for 2000 to 2012. The accident and traffic data used in the analysis come from FRA. The analysis led to several observations. There is a significant temporal decline in freight train derailment rate (-5.9% per year). The rate of change in accident rate varied by accident cause. Rates of freight train derailment caused by broken rails or welds and track geometry defects declined by 6% and 5% annually, respectively; the rate of derailment caused by bearing failure decreased by 11% annually; and rate of derailment caused by train handling errors fell by 7% annually. The regression model is used to project train derailment rates by accident causes and can be used to evaluate the safety benefit of potential accident prevention strategies. This research provides policy makers and practitioners with a statistical method for analyzing the temporal trend of train accident rate for development of rail safety policy and practice.

Rail offers a safe and efficient way to transport freight and passengers. Although rail transportation provides substantial societal benefits, train accident risks must be mitigated to the maximum extent feasible. Safety is critical for every rail system in the world. One common metric for assessing rail safety is accident rate, which is defined as the number of train accidents normalized by traffic exposure, such as train miles, car miles, gross ton-miles, or passenger miles (1-7). In the United States, data on FRA-reportable accidents (accidents whose damage cost to infrastructure, rolling stock, and signals exceeds a specified monetary threshold) and traffic exposure are reported by railroads to FRA. Using these data, the FRA publishes annual train accident rates, which have been extensively used in the development of rail safety policy and practice.

The FRA-published accident rates were based on an empirical approach that uses reported (observed) accident count data divided by the corresponding traffic exposure (e.g., millions of train miles). This empirical approach provides a high-level, preliminary assessment of

rail operational safety performance; however, it does not show whether the change in accident rate is statistically significant. Generally, the empirical accident rate analysis is subject to a statistical error called regression to the mean (RTM) (8). The RTM refers to the tendency that a random variable that deviates from the mean will return to normal given nothing has changed. 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 because of random variation, even if there is no actual safety change. For example, U.S. Class I railroad main line freight train derailment rate was 0.843 per million train miles in 2006, followed by 0.754 per million train miles in 2007. In this example, the empirical train derailment rate declined by 10% $[(0.843 - 0.754)/0.843]$. However, is this accident rate reduction statistically significant to indicate safety improvement? More generally, how should the statistical trend of train accident rates be modeled so the associated safety implications are understood? This paper addresses both questions.

METHODOLOGY

Definition of Transportation Safety

Transportation safety research communities widely accept the following notion of safety: "Safety is the number of accidents by kind and severity, expected to occur on the entity during a specified period" (8). A highlight of this notion is "the number of accidents that are expected to occur." The difference between the observed and the expected number of accidents represents the stochastic nature of accident occurrence. The following subsection illustrates a theoretical framework for modeling rail transportation safety, measured by the expected number of accidents. If the safety is measured by other metrics, the methodology can be adapted accordingly.

Statistical Theory for Modeling Train Accident Occurrence

It is assumed that each time a train enters a track segment there is a probability (p) that this train will be involved in an accident. Train accident probability is affected by infrastructure conditions, train characteristics, operational factors, environmental factors, and many other variables (1-3, 9, 10). With these conditions held constant, it can be assumed that accident probability is constant (assuming homogeneous track characteristics, rolling stock, and operational conditions within the study period). Under these assumptions, each train pass can be viewed as a Bernoulli experiment (the Bernoulli probability is denoted as p). The probability theory says that the

Department of Civil and Environmental Engineering, School of Engineering, Rutgers University, Room 607, 96 Frelinghuysen Road, Piscataway, NJ 08854. xiang.liu@rutgers.edu.

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sum of independent, identically distributed Bernoulli variables constructs a binomial distribution (11):

$$P(X = n) = \binom{N}{n} p^n (1 - p)^{N-n} \quad (1)$$

where

- n = number of train accidents,
- N = total number of train passes on a given segment during the study period, and
- p = probability that a train is involved in an accident each time it enters a segment.

Letting $p = \lambda/N$, given a large number of train passes (N is large) and relatively low accident probability (p is sufficiently small), Equation 1 can be rewritten as

$$\begin{aligned} \lim_N P(X = n) &= \lim_N \binom{N}{n} \left(\frac{\lambda}{N}\right)^n \left(1 - \frac{\lambda}{N}\right)^{N-n} \approx \frac{\lambda^n \exp(-\lambda)}{n!} \\ &= \text{Poisson}(\lambda) \end{aligned} \quad (2)$$

Equation 2 indicates that the number of train accidents within traffic exposure can be approximated by a Poisson distribution. This assumption was adopted in several previous studies (4–6, 12–15) without an explicit explanation of the rationale. In the Poisson distribution, the Poisson mean (λ) represents the expected train derailment count. Estimation of this parameter is based on sample data. Let λ^* represent an estimator of λ ; λ^* can be estimated as a function with a combination of predictor variables. The exponential function is commonly used to ensure that the estimated accident count is strictly nonnegative (4–6) (Equation 3):

$$\lambda_i^* = \exp\left(\sum_{p=0}^k b_p X_{ip}\right) M_i \quad (3)$$

where

- λ_i^* = estimated (expected) derailment count on the i th segment,
- b_p = parameter coefficient for the p th predictor variable,
- X_{ip} = p th predictor variable on the i th segment, and
- M_i = traffic exposure (e.g., train miles) on the i th segment.

Negative Binomial Regression

Several studies have been performed to determine the best functions and estimators for quantifying the statistical association between the response variable (accident count) and affecting factors (traffic exposure and infrastructure-related, equipment-related, and operational factors). Negative binomial regression (also called Poisson-gamma regression) is prevalent in the literature (4–6, 16–19). This model allows for a larger-than-the-mean variance in accident count data, and it was shown to be adequate in previous accident rate analyses (4–6, 8). In statistics, a negative binomial distribution can be interpreted as the probability distribution of the number of successes in a sequence of independent and identically distributed Bernoulli trials before a specified number of failures occur (11). In the context of rail safety, this may be interpreted as the distribution of the number of accidents given traffic exposure. Hilbe provided technical details of the negative binomial regression model and compared it with other types of regression models (20). This paper starts with this commonly used regression technique. If the negative binomial

regression model does not provide a good fit to the empirical data, other regression models will be developed.

SCOPE OF THE ANALYSIS AND DATA SOURCES

Research Scope

This research addresses the following questions:

1. Did the U.S. freight train derailment rate change between 2000 and 2012?
2. How did this change vary by accident cause?
3. What are the predicted future accident rates?
4. What are the safety implications of the results?

All the analyses in this paper were focused on freight train derailments of four U.S. Class I railroads on main tracks. Each Class I railroad has operating revenue exceeding \$378.8 million (2009 dollars). Class I railroads accounted for approximately 68% of U.S. railroad route miles, 97% of total ton-miles transported, and 94% of total freight rail revenue (21). Derailments are the most common type of FRA-reportable main line freight train accidents in the United States (22, 23).

Accident Data

FRA requires all railroads operating in the United States to submit detailed accident reports for accidents or incidents that exceeded a specified monetary threshold of damage cost to infrastructure, rolling stock, and signals. The reporting threshold is periodically adjusted for inflation and was increased to \$10,500 in 2014 (24). FRA compiles these accident reports into the rail equipment accident database, which contains information about accident location, speed, consist type, and damage cost, along with other useful information. The database has been widely used in previous rail safety studies (1, 3, 9, 10, 13, 14, 22, 23, 25–28).

Traffic Data

Data on train miles are commonly used to analyze train derailment rate (1, 3–6, 29). Railroads report to FRA their monthly train-mile data, which are available through the FRA operational data database.

RESULTS

Model

This paper focuses on the temporal trend of train derailment rate. The predictor variable is year, representing the temporal change in accident rate. The model has the following basic structure:

$$\mu_i = \exp(\alpha + \beta \times T_i) M_i \quad (4)$$

where

- μ_i = expected number of freight train derailments in year i ,
- T_i = year (for example, T_i is 2000 for the year 2000),
- M_i = millions of train miles in year i , and
- α, β = parameter coefficients.

TABLE 1 Regression Analysis Results of Final Model

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
α	122.3752	16.168	57.29	<.0001
β	-0.0612	0.0081	57.6	<.0001

NOTE: Deviance = 54.18; degrees of freedom = 50, $P = 0.32$.

This type of exponential function was used in several rail safety studies in Europe (4–6, 29). However, this statistical technique has not been widely used to analyze U.S. train accident rates. The data used for the statistical analysis include main line freight train derailments for four Class I railroads and their traffic volumes measured by train miles for 2000 to 2012.

Parameter Estimator

The parameter coefficients (α , β) were estimated with SAS commercial software. The software generates each parameter estimator and its standard error by using the maximum likelihood method in a negative binomial model (Table 1). The last column in Table 1 is the P -value of a parameter estimator, which represents the statistical significance of a predictor variable using the Wald test (20). 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 the parameter coefficient for the year variable is significantly negative ($\beta < 0$, $P < .0001$), indicating that there is a significant temporal decline in train derailment rate for all four Class I railroads.

Model Evaluation

The goodness of fit of a negative binomial model can be evaluated with a statistical criterion called deviance (20). Statistical theory says that the deviance asymptotically follows a chi-square distribution (20). On the basis of 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 (4–6, 16). Through model diagnostics, the expected number of Class I main line freight train derailments is estimated as

$$\mu_i = \exp(122.3752 - 0.0612T_i)M_i \tag{5}$$

Equation 5 is mathematically equivalent to

$$\frac{\mu_i}{M_i} = \exp(122.3752 - 0.0612T_i) \tag{6}$$

Define

$$Z_i = \frac{\mu_i}{M_i} \tag{7}$$

where Z_i is the expected freight train derailment rate per million train miles in year i .

From Equations 6 and 7, the expected train derailment rate at a specific year is estimated as follows:

$$Z_i = \exp(122.3752 - 0.0612T_i) \tag{8}$$

From Equation 8, the annual reduction in derailment rate is

$$\theta_i = \frac{Z_i - Z_{i-1}}{Z_{i-1}} = \exp(-0.0612) - 1 = -5.9\% \tag{9}$$

where θ_i is the annual percentage change in train derailment rate in year i compared with the previous year.

Equation 9 indicates that freight train derailment rates declined by an average of 5.9% annually from 2000 to 2012. If this trend continues, train derailment rates can be projected (Figure 1).

The projected (expected) train derailment rate in 2013 is 0.44 per million train miles according to the regression model based on the 2000-to-2012 trend, compared with the observed (empirical) derailment rate of 0.453 based on the FRA train safety data. This result appears to indicate a reasonable accuracy of the regression model. Further analysis can be conducted to evaluate the uncertainty in

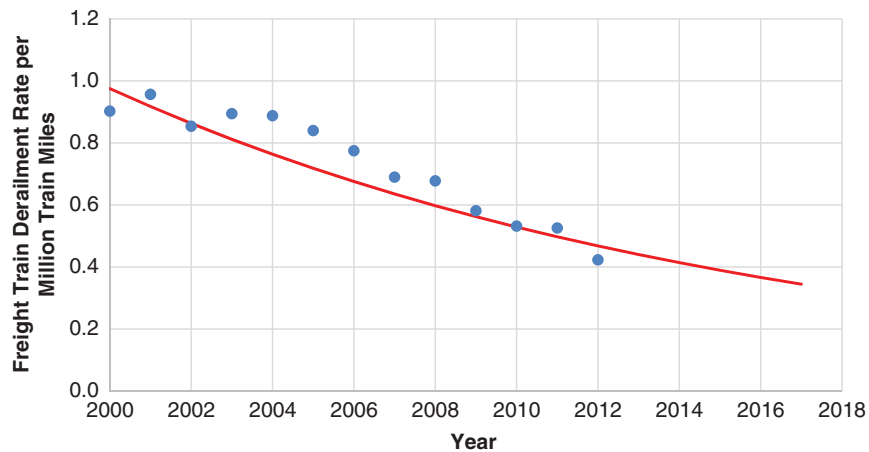


FIGURE 1 Empirical (dot) versus estimated main line freight train derailment rates (line), four Class I railroads, 2000 to 2012 (projected derailment rates for 2013 to 2017).

statistical prediction and to quantify the confidence interval of the projected accident rate. The temporal change in the overall accident rate is conceivably a net result of changing accident rate by accident cause, which is discussed in the next subsection.

Accident-Cause-Specific Train Derailment Rate

FRA specifies more than 300 accident causes accounting for a variety of circumstances and conditions that may result in train accidents (30). These causes are hierarchically organized and classified into five categories: track, equipment, human factor, signal, and miscellaneous (30). Within each of these major cause groups, 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 (30). This paper uses a variation on the FRA subgroups developed by Arthur D. Little, Inc. (ADL), in which similar cause codes were combined into groups according to expert opinions (31). ADL’s groupings are similar to the FRA subgroups but are more fine-grained, allowing greater resolution for certain causes. The ADL cause groups were used to analyze accident-cause-specific derailment frequency and severity in previous studies (13, 23, 32, 33). Broken rails or welds (08T), track geometry defects (04T), bearing

failures (10E), and train handling errors (09H) are common derailment causes on Class I main lines (22, 23), so they are used as an example in this paper to illustrate the methodology for analyzing accident-cause-specific derailment rates (Table 2). The methodology can be adapted to other accident causes as well.

For each accident cause group, a similar exponential function is developed with the negative binomial regression, as described previously:

$$Z_{ci} = \exp(\alpha_c + \beta_c T_i) \tag{10}$$

where Z_{ci} is the accident-cause-specific freight-train derailment rate per million train miles in year i .

An individual negative binomial regression model was developed for each cause group. To gain a larger sample size, the four-railroad combined derailment data by accident cause were used. The deviance test (20) shows that each regression model is adequate (Table 3).

Based on the data in Table 3, the following models are used to estimate accident-cause-specific annual train derailment rates on Class I main lines:

$$Z_{i,rail} = \exp(124.0330 - 0.0630T_i) \tag{11}$$

TABLE 2 Selected Accident Cause Groups

ADL Cause Group	FRA Cause Code	Description
08T (broken rails or welds)	T202	Broken rail–base
	T203	Broken rail–weld (plant)
	T204	Broken rail–weld (field)
	T207	Broken rail–detail fracture from shelling or head check
	T208	Broken rail–engine burn fracture
	T210	Broken rail–head and web separation (outside joint bar limits)
	T212	Broken rail–horizontal split head
	T218	Broken rail–piped rail
	T219	Rail defect with joint bar repair
	T220	Broken rail–transverse/compound fissure
	T221	Broken rail–vertical split head
	04T (track geometry defects, excluding wide gauge)	T101
T102		Cross level of track irregular (not at joints)
T103		Deviation from uniform top of rail profile
T104		Disturbed ballast section
T105		Insufficient ballast section
T106		Superelevation improper, excessive, or insufficient
T107		Superelevation runoff improper
T108		Track alignment irregular (other than buckled–sun kink)
T199		Other track geometry defects (provide detailed description in narrative)
10E (bearing failures)	E52C	Journal (plain) failure from overheating
	E53C	Journal (roller bearing) failure from overheating
09H (train handling errors, excluding braking errors) ^a	H501	Improper train makeup at initial terminal
	H502	Improper placement of cars in train between terminals
	H503	Buffing or slack action excessive, train handling
	H504	Buffing or slack action excessive, train makeup
	H505	Lateral drawbar force on curve excessive, train handling
	H506	Lateral drawbar force on curve excessive, train makeup
	H507	Lateral drawbar force on curve excessive, car geometry (short car–long car combination)
	H508	Improper train makeup
	H509	Improper train inspection
	H522	Throttle (power), improper use
	H523	Throttle (power), too rapid adjustment
	H524	Excessive horsepower
	H599	Other causes relating to train handling or makeup (provide detailed description in narrative)

^aAuthor added additional cause codes to ADL Category 09H, which originally included only H524 and H599 (32).

TABLE 3 Parameter Estimates of Accident-Cause-Specific Freight Train Derailment Rate, Class I Main Lines, 2000 to 2012

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
Broken Rails or Welds^a				
α	124.0330	22.0284	31.7	<.0001
β	-0.0630	0.011	32.87	<.0001
Track Geometry Defects^b				
α	102.7100	37.5337	7.49	0.0062
β	-0.0527	0.0187	7.93	0.0049
Bearing Failures^c				
α	223.8361	41.684	28.84	<.0001
β	-0.1132	0.0208	29.64	<.0001
Train Handling Errors^d				
α	141.8327	41.1829	11.86	0.0006
β	-0.0724	0.0205	12.44	0.0004

^aDeviance = 12.1; degrees of freedom (df) = 11; $P = .36$.
^bDeviance = 13.0; df = 11; $P = .29$.
^cDeviance = 14.0; df = 11; $P = .23$.
^dDeviance = 11.7; df = 11; $P = .38$.

$$Z_{i,geometry} = \exp(102.7100 - 0.0527T_i) \tag{12}$$

$$Z_{i,bearing} = \exp(223.8361 - 0.1132T_i) \tag{13}$$

$$Z_{i,handling} = \exp(141.8327 - 0.0724T_i) \tag{14}$$

where

- $Z_{i,rail}$ = expected broken rail-caused train derailment rate per million train miles,
- $Z_{i,geometry}$ = expected track geometry defect-caused train derailment rate per million train miles,
- $Z_{i,bearing}$ = expected bearing failure-caused train derailment rate per million train miles, and
- $Z_{i,handling}$ = expected train handling error-caused train derailment rate per million train miles.

The empirical and estimated train derailment rates for the four accident causes were compared (Figure 2). Broken rails had a higher derailment rate than the other accident causes, highlighting the importance of prevention of broken rail (14, 22, 23). The annual rate of change in accident-cause-specific derailment rate is estimated as follows:

- Broken rails or welds, -6%;
- Track geometry defects (excluding wide gage), -5%;
- Bearing failures, -11%; and
- Train handling errors (excluding braking errors), -7%.

The analysis shows that bearing failures and train handling errors had a higher percentage reduction in annual derailment rate, compared with track geometry defects and broken rails within the same study period. The temporal trends of accident-cause-specific derailment rates were compared (Figure 3). Given these trends, broken rails may continue to be leading derailment causes. Bearing failures had a higher derailment rate than train handling errors until 2010 but have had a lower derailment rate since then, in part because the rate of bearing failure-caused derailments is declining faster (11% reduction per year).

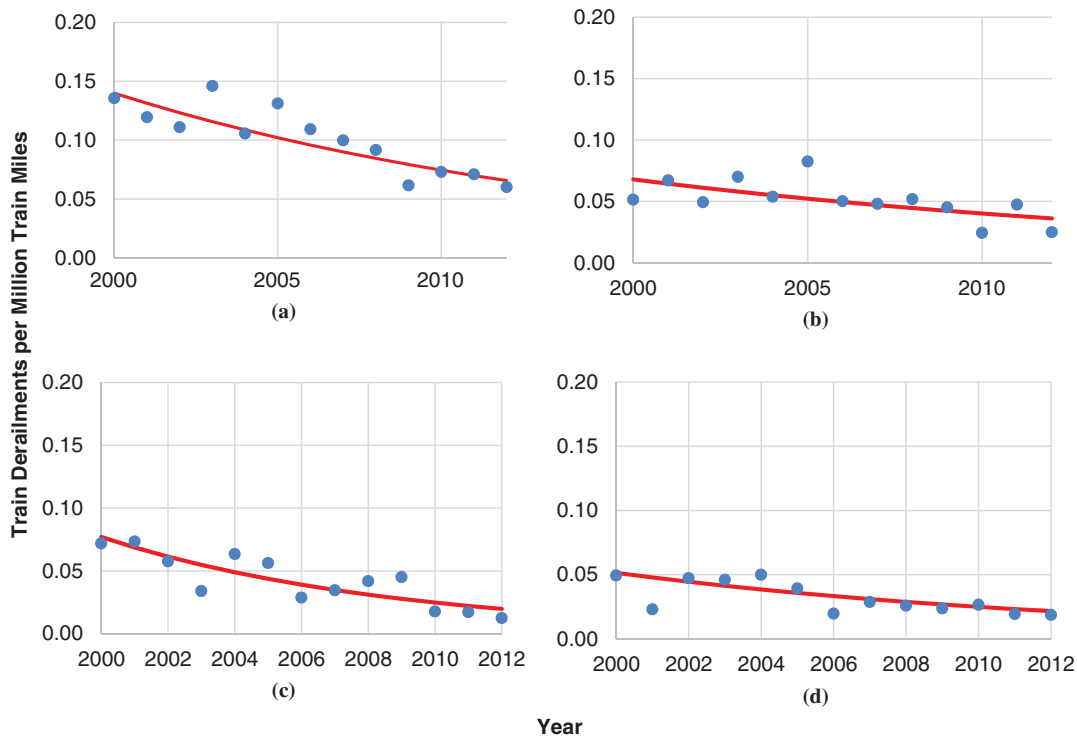


FIGURE 2 Class I railroad freight train derailment rate on main lines by accident cause, 2000 to 2012: (a) broken rails or welds, (b) track geometry defects (excluding wide gage), (c) bearing failures, and (d) train handling errors.

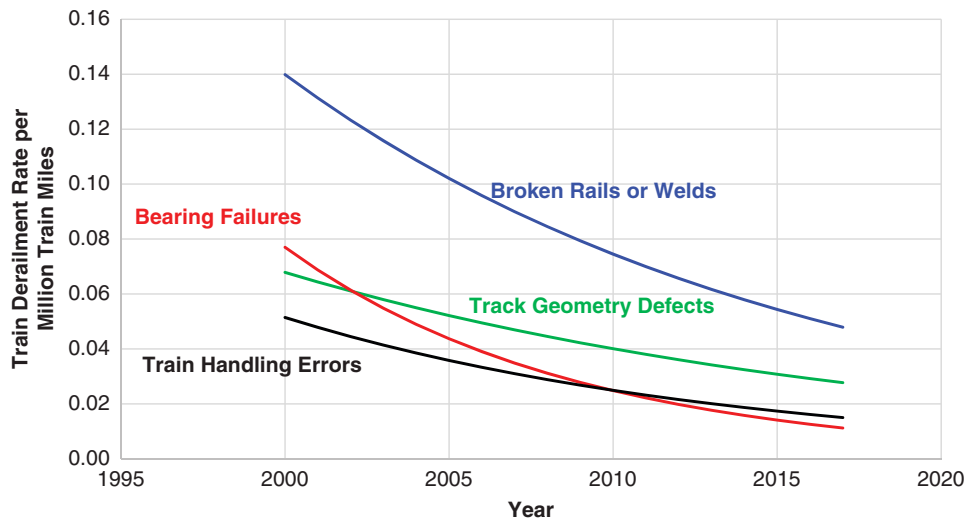


FIGURE 3 Temporal trend of freight train derailment rate by accident cause (projected derailment rates for 2013 to 2017).

DISCUSSION OF RESULTS

In this section, implications of this research for rail transportation safety and risk analysis are discussed.

Temporal Change in Rail Safety

This research found that the overall freight train derailment rate on U.S. Class I railroad main lines declined by 5.9% annually from 2000 to 2012. This change may in part be a result of continued investment in infrastructure and rolling stock, safety culture, operations, training and education, research, and other safety initiatives. The analysis also found that annual derailment rates are statistically identical among the four Class I freight railroads. However, the change of derailment rate could vary by accident cause. The top two train derailment causes (broken rails and track geometry defects) had similar declining rates (approximately 5% to 6% annual reduction), whereas bearing failure–caused train derailment rate had a more significant decline (11% annual reduction).

Implications for Transportation Risk Analysis

Many train safety and risk analyses were based on the average accident rate information within a multiyear study period. Because of the declining accident rate, use of the average accident rate may not represent up-to-date rail operational safety. An adjustment factor may be needed for estimating the most recent accident rate according to historical safety trends when no better information is available. In the long run, risk analysis for rail safety should be revisited periodically and revised to reflect changes in accident rate and other risk factors.

ONGOING RESEARCH

Causal Analysis of Train Derailment Rate

The intent of this research was exploratory rather than explanatory. That is, this work focused on identifying the temporal trend, instead of explaining why it exists. The causal relationship between train

accident rate and affecting factors requires future research to gain a better understanding of the causal factors of rail safety and how changing these factors may affect safety (25).

Analysis of Train Derailment Severity

This paper focused on train derailment rate (likelihood). Train derailment severity (e.g., number of cars derailed, property damage, casualties) also is critical in railroad safety and risk analysis (22, 23). Train derailment severity may vary by accident cause, accident speed, train length, and other factors (10). The next step of this work is to incorporate train derailment severity into a larger rail safety management framework.

Analysis of Crude Oil Transportation Risk

This study included all types of train accidents. Of recent interest is the rate of crude oil train accidents. The negative binomial regression model described in this paper can be used to model the temporal variation in crude oil train accident rate and thus evaluate the safety trend before and after the implementation of certain safety improvement strategies.

CONCLUSION

A statistical methodology was developed for modeling the temporal trend of U.S. Class I railroad freight train derailment rates on main lines from 2000 to 2012. Within the study period, the analysis shows that the national freight train derailment rate decreased by 5.9% per year. Broken rails or welds were the leading derailment cause, and the derailment rate for this cause declined by 6% per year. Track geometry defects, bearing failures, and train handling errors all had declining train derailment rates, among which the derailment rate reduction caused by bearing failures was more substantial, at an 11% reduction per year. For 2017, the projected overall train derailment rate is about 0.34 per million train miles (a 64% reduction compared to 2000) if the current safety trend continues. The time-varying accident rate should be taken into account in train safety and risk analyses and decisions.

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