Statistical Analysis of Seasonal Effect on Freight Train Derailments

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Abstract: Freight train accidents can damage infrastructure and rolling stock, disrupt operations, and possibly cause casualties and harm the environment. Understanding accident risks associated with major accident causes is an important step toward developing and prioritizing effective accident prevention strategies. This paper developed a negative binomial regression model to estimate freight-train derailment frequency on Class I railroad mainlines, accounting for derailment accident cause, traffic exposure, railroad, and season. The primary focus is to quantitatively measure the seasonal effect on freight-train derailment frequencies given traffic exposure. For model illustration, the analysis focused on three common derailment causes on freight railroads: broken rails, broken wheels, and track buckling, using the empirical Federal Railroad Administration (FRA)-reportable freight railroad derailment data on mainlines gathered between 2000 and 2016. The modeling results show that it tends to have high derailment rates in winter due to broken rails and broken wheels (double that of summer), whereas summer has the highest likelihood of buckling-caused derailment of all of the seasons (e.g., 6 times that of spring and 10 times that of fall). These analytical results can contribute to the risk-based optimization of rail and wheel inspection frequency. The statistical modeling methodology developed in this paper can be adapted to other types of train accidents or accident causes, ultimately supporting the optimal allocation of train safety improvement resources. **DOI: 10.1061/JTEPBS.0000583.** *© 2021 American Society of Civil Engineers.*

Author keywords: Freight train; Derailment; Accident frequency; Season; Broken rails.

Introduction and Research Objective

The 140,000–track-mile freight railroads in the United States provide productive and cost-efficient freight services, supporting \$219 billion in economic output and generating around \$26 billion in tax revenue in 2017 (AAR 2020). Safety is of paramount importance. Derailment is a common type of freight-train accident on US railroads (Barkan et al. 2003; Liu 2017). Derailment analysis and prevention have long been a high priority for the railroad industry and the Federal Railroad Administration (FRA) of the United States. There are various factors affecting derailment risks, one of which is the seasonal effect.

The primary research objective of this paper is to quantitatively understand the seasonal effect on freight-train derailment frequencies for major causes, particularly broken rails, broken wheels, and buckled tracks. The analysis includes four major freight train railroads in the United States: Burlington Northern and Santa Fe Railway (BNSF), CSX Transportation (CSX), Norfolk Southern Railway (NS), and Union Pacific Railroad (UP). Several research questions will be addressed in this study:

How do derailment frequencies, given traffic exposure, vary by season for each derailment accident cause?

Does the seasonal effect on derailment frequencies, given traffic exposure, also vary by railroad?

What is the proper statistical analysis technique to fit empirical derailment data, considering multiple influencing factors?

To address these questions, a statistical technique called negative binomial regression was used to fit the empirical derailment data, accounting for railroad, season, derailment accident causes, and traffic volume. This study developed a novel application of the negative binomial regression model to identify and quantify the seasonal effect on Class I railroads, accounting for derailment cause, traffic exposure, and railroad. Seasonal temperature changes may modify the dynamic behavior of the railroad components and have a significant effect on the infrastructure response (Salcher et al. 2016). Previous studies (Gonzales et al. 2013; Salcher et al. 2016) have revealed a high impact of the surrounding air temperature on the structural stiffness based on long-term measurements. In other words, the decreasing or increasing temperature leads to an increase or decrease of stiffness. However, these prior research activities focused on the micro-level mechanism analysis of the seasonal effect on rail safety based on physical models or mathematical models. This paper provides a macro-level evaluation of seasonality in freight-train derailments. Moreover, the general approaches and methodologies in this paper can be adapted to other types of accidents or accident causes. The statistical analysis procedure can be used as a long-term reference for railway researchers to understand the relationship between derailment risks and influencing factors on various spatial and temporal scales. The remainder of this paper is organized as follows. It begins with a review of relevant research and continues by identifying knowledge gaps that warrant this study. Next, the statistical modeling technique and the data used to fit the model are introduced. Finally, insights from the statistical data analysis are drawn, and possible future research directions are suggested.

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Note. This manuscript was submitted on February 19, 2021; approved on May 24, 2021; published online on August 11, 2021. Discussion period open until January 11, 2022; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering, Part A: Systems***, © ASCE, ISSN 2473-2907.

Literature Review

Accident Causes

FRA train accident causes are systematically organized and categorized by the FRA into five major cause groups: track, equipment, human factor, signal, and miscellaneous causes (FRA 2011). Each accident cause describes a specific circumstance or contributing factor that may lead to a train accident. Previous studies found that track failures (e.g., broken rails, track geometry defects, buckling) are among the most common and severe derailment causes on US railroads (Barkan et al. 2003; Liu et al. 2012; Liu 2017; Ghofrani et al. 2021), probably due to cyclic high-load impact from heavy-haul rail operations (Liu and Dick 2016). To conduct further investigation of track failures, Ghofrani et al. (2021) developed a quantitative analysis of impact factors behind the occurrence of service failures based on data collection from a Class I US railroad from 2011 to 2016. Furthermore, extensively used equipment may lead to mechanical problems, such as broken wheels due to thermal stress, high-impact loads, and interactive forces on tracks. Similarly, the causes of collisions and highway-rail grade crossing were also studied in previous research. Human errors were identified as the main causes of train collisions (Evans 2011; Liu 2017; Turla et al. 2019).

Derailment Rate Influencing Factors

Derailment is a common type of accident on freight railroads. Derailment risk factors have been studied based on historical data. The prior literature has analyzed derailment frequency and rate by train speed (Yang et al. 1973; Zhang and Liu 2020), FRA track class (Anderson and Barkan 2004; Liu et al. 2017), train length (Anderson and Barkan 2004; Schafer and Barkan 2008), and seasonal effect (Liu et al. 2013a). Among these factors, seasonal effect, which is related to the objective of this paper, is reviewed in more detail. A prior study (Liu et al. 2013a) speculated that there may be seasonal effects on broken-rail–caused derailments. Tensile thermal stresses in colder climates may accelerate the occurrence of rail breaks from small rail defects. On the other hand, the probability of identifying rail breaks using a track circuit increases in the winter due to thermal contraction. Seasonal variation was also recognized based on the data from wheel impact load detectors (Liu et al. 2013a; Van Dyk et al. 2013). In the statistical causal analysis of freight-train derailments, Liu (2017) concluded that fall and winter appear to have a higher likelihood of a broken-rail–caused derailment than spring and summer, given the same railroad and traffic level. Instead, track-geometry-defect–caused derailments (excluding buckling-caused derailments) occur more frequently in spring and summer than in fall and winter, all else being equal. Moreover, Dobney et al. (2010) stated that a number of infrastructure failures were caused by high summer temperatures, in which hot temperatures cause the metal of the rail to expand, resulting in a deformation of the track due to high compressive forces. Although continuous welded rail is prestressed to withstand a reasonable temperature range based on local climate, if the temperature is extremely high and the track is incorrectly stressed, or just in poor condition, then buckles are more likely to occur (Dobney et al. 2010). Sanchis et al. (2020) developed a Monte Carlo simulation to analyze the vulnerability of the Spanish high-speed rail network with increasing temperatures for both annual and seasonal averages. In addition to highlighting the vulnerability of the Spanish rail network with the anticipated buckling occurrences, this study also disclosed the relevant variations in different climates and time horizon scenarios in Spain.

Derailment Data Analysis Approaches

The empirical approach and statistical model are the two commonly used approaches to analyzing derailment data. The high-level rail operational safety analyses in some published papers and FRA-published accident reports were generally based on empirical approaches. Based on historical train accident data, it was found that derailments accounted for 72% of all types of accidents on mainlines (Liu 2017), and more than 70% of derailments were caused by infrastructure or rolling stock failures (Liu et al. 2012). In the European Union, derailment is illustrated to be the most commonly occurring type of train accident (Dindar et al. 2018). Nevertheless, the empirical approach has limitations in dealing with the randomness of accident occurrence (Liu 2015). Alternatively, the statistical model is widely used to quantify the statistical association between accident risk and affecting factors. The negative binomial regression model has been developed in the literature to estimate accident frequencies and rates in railways (Evans 2011; Liu et al. 2013b; Liu 2015) and highways (Miaou 1994; Chang 2005). The negative binomial regression is a special type of generalized linear model for modeling Poisson-distribution data. This regression model was shown to provide a good fit with the empirical accident data.

Knowledge Gaps

To the authors' knowledge, limited prior research has explicitly examined the seasonal effect on derailment frequencies of freight railroads in the United States. The literature suggests that derailment frequencies due to certain accident causes might have seasonal variations. Nevertheless, there is a lack of statistical methodology to quantitatively analyze cause-specific derailment frequencies given traffic exposure with a particular interest in the seasonal effect. A clear understanding of seasonal variation in freight-train derailment can support the optimal allocation of safety improvement resources. In addition, most prior research has focused on nationwide aggregated safety statistics without considering railroad-specific derailment frequencies given traffic exposure. To narrow these knowledge gaps, this paper aims to develop novel statistical models to understand the seasonal effect on derailment frequencies in conjunction with accident causes and railroads.

Data Sources

Train Derailment Data

Derailment data in this study come from the FRA Rail Equipment Accident (REA) database (6,180.54). Railroads are required to submit accident reports of all accidents that exceed a monetary threshold for damage and loss in an accident. The reporting threshold for the REA is periodically adjusted for inflation and increased from \$6,600 in 2000 to \$10,500 in 2016 (FRA 2015). The data include freight-train derailments on the mainlines of Class I railroads from 2000 to 2016.

Traffic Exposure Data

Railroad traffic exposure is used to calculate the derailment rate, which is defined as the number of derailments normalized by traffic volume (Evans 2011; Liu 2017; Zhang and Liu 2020). Train-miles and car-miles are two common traffic metrics, each of which corresponds to certain types of accident causes. The prior study finds that some accident causes are more related to train-miles, including most human error, whereas most equipment causes and infrastructure failure causes are more related to car-miles (Schafer and Barkan 2008). There are two publicly accessible traffic volume data sources: the FRA Operational Database (6,180.55) and the Class I Railroad Annual Reports (Form R-1) from the Surface Transportation Board (STB). The information from the FRA Operational Database is the monthly train-mile data reported by the railroads. Annual car-miles and train-miles of each Class 1 railroad are available on the R-1 Form on the STB website (STB 2017). Because the STB database does not provide monthly car-mile data, we estimate monthly car-mile data using the distribution of monthly train-mile data from the FRA Operational Database. For example, if 10% of annual train-miles occur in January (from FRA Operational Database), it is assumed that 10% of annual car-miles also occur in January. This assumption might be valid if there is no significant variation in train length in the different months within 1 year. The same assumption was made in a prior study (Liu 2017). Railroads can update the analysis based on their actual car-mile data for each month when they use the model developed in this paper.

Explanatory Variables

Season

To identify the seasonal effect on freight-train derailment frequencies given traffic exposure, derailment count and traffic volume are divided into four seasons. In this study, the season "spring" includes March through May, "summer" includes June through August, "fall" includes September through November, and "winter" includes December through February. If a different temporal delineation is used, the model can be modified accordingly.

Railroad

Nationwide statistics on railroad safety were studied exclusively in the literature. However, few studies have considered railroad-specific derailment frequencies given traffic exposure by risk factors. Among around 600 freight railroads operating in the United States, the four largest freight railroads, UP, BNSF, NS, and CSX, account for around 86% of the revenue and 63% of the track mileage in 2016 (AAR 2020). To preserve railroad-specific information, we used E1 and E2 to denote the two eastern railroads (CSX and NS) and W1 and W2 to denote the two western railroads (BNSF and UP).

Accident Cause

A variation on the FRA cause group was developed by Arthur D. Little (ADL) in the early 1990s, based on railroad engineering and mechanical experts (ADL 1996). ADL's groupings are similar to the FRA's subgroups but allow greater resolution for certain causes. For example, broken rails, joint bars, and rail anchors that are combined in the same FRA subgroup are distinguished from broken rails or welds and joint bar defects in the ADL grouping. In some cases, ADL also combined similar cause subgroups into one group. With these features, derailment causal groups developed by ADL are used in the study of train safety and risk analysis (Schafer and Barkan 2008; Liu et al. 2012; Lin et al. 2014; Liu 2017). In this cause-specific study, the analysis focused on three major derailment causes (Table 1): broken rails (08T), broken wheels (12E), and buckled track (05T), all of which are among the most common derailment causes on US freight railroads (Liu 2017).

Table 1. Derailment cause grouping

ADL cause group	FRA cause code	Description
Broken rails or welds (08T)	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-horizon split head
	T218	Broken rail-piped rail
	T219	Rail defect with joint bar repair
	T220	Broken rail-transverse or compound fissure
	T221	Broken rail-vertical split head
Broken wheels (12E)	E60C	Broken flange
	E61C	Broken rim
	E62C	Broken plate
	E63C	Broken hub
	E6AC	Thermal crack, flange, or tread
Buckled track (05T)	T109	Track alignment irregular (buckled or sunkink)

Empirical Derailment Frequency and Derailment Rate

Based on the empirical observations from all cause-combined derailments and traffic volumes, there are insignificant differences among the four seasons in derailment frequencies given traffic exposure that is measured by either train-miles or car-miles (see Appendix). In terms of cause-specific derailments, only derailment rate defined as the number of derailments per car-miles was analyzed because the three studied ADL cause groups, as equipment causes or infrastructure failure causes, are more related to car-miles. Fig. 1 shows the empirical distribution of freight-train derailment frequencies given traffic exposure by railroad (two eastern Class I railroads combined and two western Class I railroads combined for illustrative convenience) in three major cause groups. There were no buckled-track–caused derailments in winter during the study period. For each derailment cause, the empirical data show some level of seasonal variation in terms of derailment frequencies. Also, for the same cause, the western railroads and eastern railroads may have different derailment rates. In the next section, all these empirical observations will be statistically investigated using negative binomial regression modeling.

Derailment Frequency Modeling

Methodology

This paper aimed to estimate the occurrence of Class I mainline railroad freight-train derailments in the United States. Poisson regression is often used for modeling accident count data, but it theoretically requires the variance of the dependent variable to be equal to its mean (Greene 1994). As a generalization of Poisson regression, negative binomial regression has an extra parameter to model the overdispersion (variance is greater than the mean). In the past, negative binomial regression has been widely used to model accident frequency data (Evans 2011; Wei and Lovegrove 2013; Liu 2017). Therefore, it was used as an initial method. The results

J. Transp. Eng., Part A: Systems, 2021, 147(10): 04021073

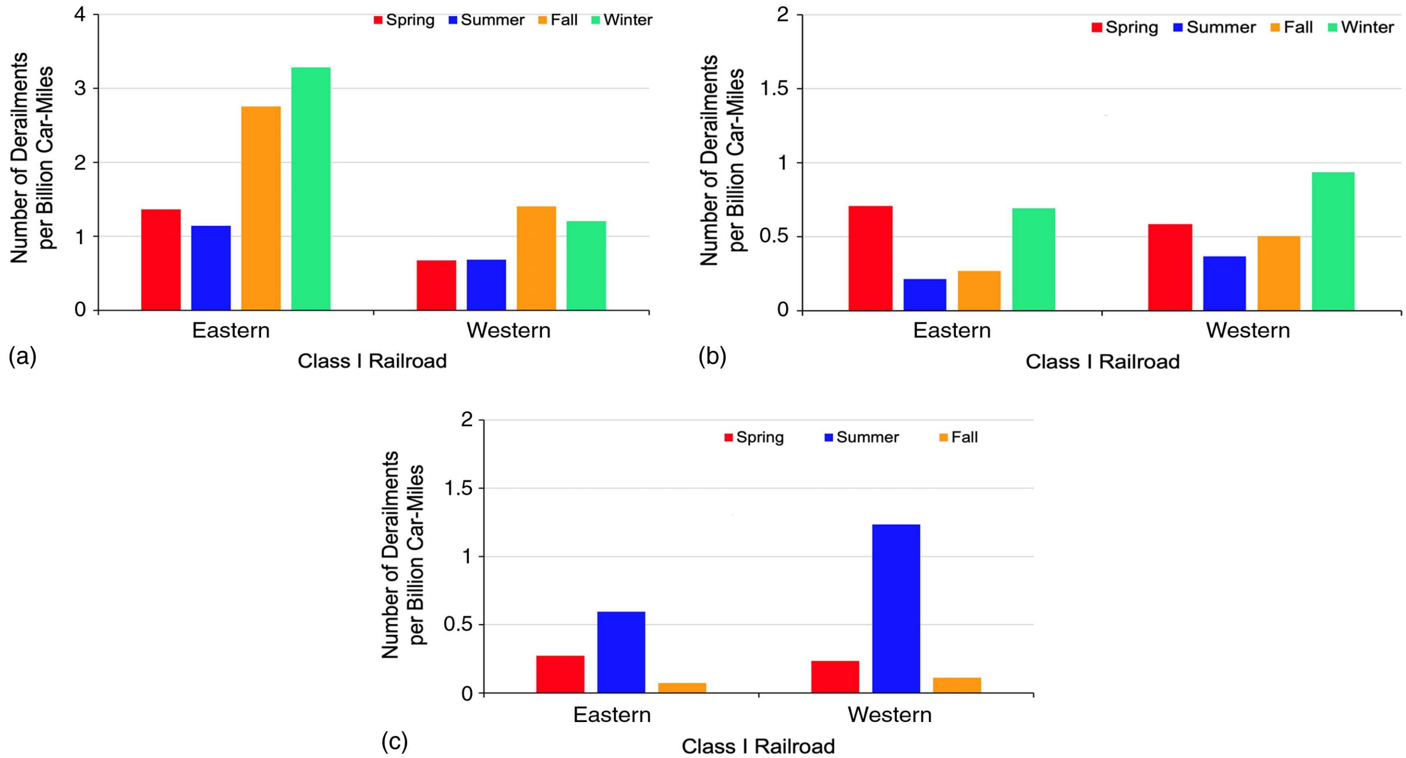

Fig. 1. Empirical mainline derailment frequency given traffic exposure by cause and railroad, 2000 to 2016: (a) broken rails; (b) broken wheels; and (c) buckled track.

showed that the estimated freight-train derailment frequency using negative binomial regression well fit the empirical data based on Pearson's goodness-of-fit test. Negative binomial regression is also simple and easy to implement. Because of these reasons, the results of this paper are based on the negative binomial regression model. In future work, alternative methods might be considered depending on data availability.

Chang (2005) concluded that previous research employed negative binomial regression models and other statistical models in analyzing derailment frequencies with two motivations. First, the occurrence of transportation accidents can be regarded as a random event. Second, negative binomial regression is able to identify a broad range of risk factors that significantly contribute to accidents. The negative binomial regression model associates the number of accidents with influencing factors and traffic exposure. The parameter coefficients are fitted to maximize the likelihood function (Agresti and Kateri 2011). Specifically, negative binomial regression assumes that the observed data is modeled as a Poisson variable with a mean of λ_i, and the model error follows a gamma distribution. Thus, the negative binomial regression model is also called the Poisson–gamma model, in which the dependent variable follows a mixture of two distributions (Liu et al. 2013b; Zhang and Liu 2020). The basic framework is as follows:

$$g(y_i;\lambda_i) = \frac{e^{-\lambda_i}\times\lambda_i}{y_i!} \tag{1}$$

$$k(\lambda_i|\psi,\mu_i) = \frac{(\psi/\mu_i)^{\psi}}{\Gamma(\psi)}\lambda_i^{\psi-1}e^{-\frac{\lambda_i}{\mu_i}\psi} \tag{2}$$

$$\mu_i = \exp\left(b_0 + \sum_{m=1}^{k} b_{mi}X_{mi}\right)M_i \tag{3}$$

where y_i = observed number of derailments for group i; λ_i = mean of the Poisson distribution for group i; $g(y_i;\lambda_i)$ = probability density function of Poisson (λ_i) or $y_i|\lambda_i \sim \text{Poisson}(\lambda_i)$; $k(\lambda_i|\psi,\mu_i)$ = probability density function of $\text{Gamma}\left(\psi,\frac{\psi}{\mu_i}\right)$, or $\lambda_i|\psi \sim \text{Gamma}\left(\psi,\frac{\psi}{\mu_i}\right)$; μ_i = estimated number of derailments for group i; ψ = inverse dispersion parameter; $b_{mi} = m$th parameter coefficient for group i; $X_{mi} = m$th explanatory variable for group i; and M_i = traffic exposure for group i.

In this paper, the negative binomial regression model was developed to model freight train derailment frequencies. Other regression models would be used if the negative binomial regression did not fit the empirical data well. The freight-train derailments across the total traffic volume for a specific cause are assumed to follow a negative binomial distribution. The functions of railroad index, season index, and traffic volume in the negative binomial regression model are as follows:

$$\mu_i = \exp(\alpha_{i0} + \alpha_{i1}\text{Railroad} + \alpha_{i2}\text{Season} + \alpha_{i3}\text{Railroad}\times\text{Season}) \times \text{Traffic} \tag{4}$$

where μ_i = derailment frequency for a specific cause i; α_{i0}, α_{i1}, α_{i2}, α_{i3} = parameter coefficients for a specific derailment cause i; Railroad = railroad indicator, E1, E2, W1, W2; Season = season indicator, representing spring, summer, fall, winter; and Traffic = traffic volume (billion car-miles).

Eq. (4) considers the main effects for season and railroad, as well as the interaction effect between these two categorical variables. In two categorical variables, railroad and season, W2 and winter are set as the reference category, respectively. Thus, α_{i1} represents the difference between the reference railroad (W2) and other railroads, and α_{i2} indicates the difference between winter and

Table 2. Variable selection in the model

Variables	Degree of freedom	Chi-square	Pr > Chi
Broken rails (08T)			
Railroad	3	132.49	<0.001
Season	3	98.61	<0.001
Railroad × season	9	10.74	0.294
Broken wheels (12E)			
Railroad	3	19.78	0.002
Season	3	41.21	<0.001
Railroad × season	9	14.67	0.100
Buckled track (05T)			
Railroad	3	40.15	<0.001
Season	2	144.84	<0.001
Railroad × season	6	6.39	0.381

other seasons. The two-factor interaction term Railroad × Season tests whether the association between derailment frequency given traffic exposure and season also depends on the railroad. Put another way, if the parameter coefficient α_{i3} is not equal to 0, the seasonal effect on derailment frequency given traffic exposure also varies differently by railroad. Also, to validate the practicability of negative binomial regression, the mean and variance of the observed derailment frequency are also calculated. The ratios of variance to mean in broken rails (9.8), broken wheels (8.6), and buckled track (32.1) are all greater than 8, which indicate the overdispersion features in interested derailment groups.

Results of the statistical significance test are listed in Table 2. The significance of a variable relies on the corresponding P-value. If the P-value is less than 0.05, it indicates that the variable is statistically significant and thus should be included in the model. Otherwise, if the P-value is larger than 0.05, it indicates that a variable is statistically insignificant and thus should be excluded. Table 2 shows that, among three major derailment causes, the interaction terms between railroad and season parameter are statistically insignificant (P-value = 0.294, 0.100, and 0.381, respectively, all above 0.05). This means that for each cause, the seasonal effect on derailment frequency given traffic exposure is consistent along the four Class I railroads. In other words, if winter has a higher rate than summer for a certain cause in one railroad, the same phenomenon can be found in other railroads as well. Because there is no interaction between the railroad and season variables, the Railroad × Season interaction variable will be removed from the final model. In the empirical data, there were zero track-buckling–caused derailments in winter. Therefore, only spring, summer, and fall are considered in the model for this cause.

Model Calibration

Based on the aforementioned discussion in the model framework, as well as derailment data and traffic exposure, the parameter coefficients in negative binomial regression models can be estimated by maximizing the likelihood function (Liu 2017).

Regression analysis results of the final model for each derailment cause are shown in Table 3. In this table, the last column is the P-value of a parameter coefficient that represents the statistical significance in relation to the reference level. For example, for broken-rail–caused derailments, the P-values for the parameter coefficient of all three railroads are less than 0.05, indicating that there is a statistical difference between W2 and any of the other railroads in terms of derailment frequency, all other factors (e.g., season, traffic volume) being the same. Similarly, there is no statistical

Table 3. Parameter coefficient estimates

Parameter	Estimate	Standard error	95% confidence interval		P-value
			Upper	Lower	
Broken rails (08T)					
Intercept	0.074	0.099	−0.124	0.264	0.453
Railroad					
E1	1.175	0.107	0.967	1.386	<0.001
E2	0.724	0.123	0.482	0.965	<0.001
W1	0.408	0.106	0.203	0.617	<0.001
W2 (reference)	0	0	0	0	—
Season					
Spring	−0.700	0.110	−0.919	−0.487	<0.001
Summer	−0.823	0.113	−1.049	−0.603	<0.001
Fall	−0.017	0.090	−0.193	0.160	0.854
Winter (reference)	0	0	0	0	—
Broken wheels (12E)					
Intercept	0.022	0.117	−0.215	0.245	0.854
Railroad					
E1	−0.815	0.216	−1.260	−0.409	<0.001
E2	0.042	0.166	−0.291	0.361	0.801
W1	−0.215	0.132	−0.475	0.043	0.103
W2 (reference)	0	0	0	0	—
Season					
Spring	−0.319	0.142	−0.599	−0.042	0.025
Summer	−0.997	0.176	−1.352	−0.660	<0.001
Fall	−0.681	0.159	−0.997	−0.374	<0.001
Winter (reference)	0	0	0	0	—
Buckled track (05T)					
Intercept	0.441	0.110	0.217	0.651	<0.001
Railroad					
E1	−0.365	0.200	−0.770	0.015	0.067
E2	−1.923	0.421	−2.864	−1.185	<0.001
W1	−0.606	0.166	−0.935	−0.285	<0.001
W2 (reference)	0	0	0	0	—
Season					
Spring	−1.423	0.188	−1.807	−1.066	<0.001
Summer (reference)	0	0	0	0	—
Fall	−2.336	0.280	−2.930	−1.825	<0.001

difference between fall and winter for broken-rail-caused derailments because the P-value for fall is 0.854. As a study focusing on the dependent variable (e.g., estimated derailment frequency), the models of three causal groups of this study keep both significant variables and insignificant variables. Meanwhile, the insignificant difference of two independent variables should also be disclosed with minimum coefficients. The equations of estimated derailment frequency by cause involving both significant variables and insignificant variables are as follows:

- Broken rails (08T)

$$\mu_1 = \exp(0.074 + 1.175X_{\mathrm{E1}} + 0.724X_{\mathrm{E2}} + 0.408X_{\mathrm{W1}} - 0.700X_{\mathrm{Spring}} - 0.823X_{\mathrm{Summer}} - 0.0166X_{\mathrm{Fall}}) \times \mathrm{Traffic} \quad (5)$$

- Broken wheels (12E)

$$\mu_2 = \exp(0.022 - 0.815X_{\mathrm{E1}} + 0.042X_{\mathrm{E2}} - 0.215X_{\mathrm{W1}} - 0.319X_{\mathrm{Spring}} - 0.994X_{\mathrm{Summer}} - 0.681X_{\mathrm{Fall}}) \times \mathrm{Traffic} \quad (6)$$

J. Transp. Eng., Part A: Systems, 2021, 147(10): 04021073

- Buckled track (05T)

$$\mu_3 = \begin{cases} \exp\begin{pmatrix} 0.441 - 0.365X_{E1} - 1.923X_{E2} - 0.606X_{W1} \\ -1.423X_{Spring} + 0 \cdot X_{Summer} - 2.336X_{Fall} \end{pmatrix} \times \text{Traffic} & \text{other seasons} \\ 0 & \text{winter} \end{cases} \quad (7)$$

where μ_i = estimated derailment frequency for a specific cause i; $X_{E1} = \begin{cases} 1, & \text{if the railroad is E1} \\ 0, & \text{otherwise} \end{cases}$, similar notations for X_{E2}, X_{W1}; $X_{Spring} = \begin{cases} 1, & \text{if the season is spring} \\ 0, & \text{otherwise} \end{cases}$, similar notations for X_{Summer}, X_{Fall}; and Traffic = traffic volume (billion car-miles).

With Eqs. (5)–(7), for each derailment cause, derailment frequency in a specific season and railroad can be estimated with the consideration of traffic volume. The ratio of derailment frequency to traffic exposure represents the derailment rate. For example, for railroad W1, there were a total of 52 billion car-miles in spring between 2000 and 2016. The estimated number of derailments due to broken rails is calculated using Eq. (6)

$$\mu_2 = \exp(0.074 + 0.408(X_{W1} = 1) - 0.700(X_{Spring} = 1)) \times 52 = 42$$

The actual number of broken-rail–caused derailments occurring in this season during the study period was 43, which is very close to the model estimation.

Model Validation

Table 4 lists empirical versus predicted derailment frequency by season for three derailment causes. Overall, the prediction accuracy is reasonably adequate using the negative binomial regression models. Furthermore, we develop a Pearson's test (Agresti and Kateri 2011) to evaluate the degree of model fit to empirical data, using the information from Table 4.

Pearson's goodness-of-fit test, which asymptotically approaches a χ^2 distribution, is defined by

$$\chi^2 = \sum_{i}^{N} \frac{[n(i) - \hat{m}(i)]^2}{\hat{m}(i)} \quad (8)$$

where N = number of categories; ni = number of observed derailments in the ith category; and $\hat{m}i$ = estimated number of derailments in the ith category.

Pearson's test shows that the P-values are all greater than 0.05 for each cause (P-value = 0.76 for broken rails; P-value = 0.60 for broken wheels; P-value = 0.66 for buckled track). Overall, the developed negative binomial regression model adequately fits the empirical data for each derailment cause.

Discussion

Conditional Odds Ratio for Interpreting Seasonal Effect

The conditional odds ratio (COR) is a useful output of the negative binomial regression model. For example, in derailments caused by

Table 4. Model estimation versus observation on mainlines, 2000 to 2016

		Broken rails		Broken wheels		Buckled track	
Railroad	Season	Observed	Predicted	Observed	Predicted	Observed	Predicted
E1							
	Spring	38	38	9	7	9	6
	Summer	32	36	5	4	22	25
	Fall	75	74	3	4	3	2
	Winter	82	78	9	9	0	0
E2							
	Spring	22	21	22	15	3	1
	Summer	16	18	4	7	3	4
	Fall	38	40	8	10	0	0
	Winter	46	41	18	19	0	0
W1							
	Spring	43	42	26	31	8	10
	Summer	46	38	22	16	47	44
	Fall	79	82	26	22	4	4
	Winter	73	79	35	40	0	0
W2							
	Spring	23	25	31	34	15	17
	Summer	21	22	14	17	74	71
	Fall	60	49	24	24	7	7
	Winter	39	47	52	45	0	0
Total		733	730	308	304	195	191

J. Transp. Eng., Part A: Systems, 2021, 147(10): 04021073

Table 5. COR of broken-rail–caused derailment by season and railroad

Conditional odds ratio	08T Broken rails
μ_{E1}/μ_{W2}	3.24 (2.63, 3.99)
μ_{E2}/μ_{W2}	2.06 (1.61, 2.62)
μ_{W1}/μ_{W2}	1.50 (1.22, 1.85)
$\mu_{\text{spring}}/\mu_{\text{winter}}$	0.50 (0.39, 0.61)
$\mu_{\text{summer}}/\mu_{\text{winter}}$	0.44 (0.35, 0.54)
$\mu_{\text{fall}}/\mu_{\text{winter}}$	0.98 (0.82, 1.17)

Note: The values in parentheses are the 95% confidence interval of COR.

broken rails, the COR for spring versus winter is 0.50, which means that, given the same railroad and traffic volume, the derailment frequency in spring is 50% of that in winter, with a 95% confidence interval between 0.39 and 0.61. Similar comparative results can be evaluated showing that summer involves an even lower derailment frequency, which is only 44% of that in winter. If the confidence interval of COR contains 1, there is no statistical difference between the reference and compared levels. For example, in Table 5, $\mu_{\text{fall}}/\mu_{\text{winter}}$ is equal to 0.98, with a 95% confidence interval of COR between 0.81 and 1.17. Because the confidence interval contains 1, it indicates that there is no statistical difference between fall and winter in terms of broken-rail–caused derailment frequency given traffic exposure for each railroad.

Using the COR statistics, the following observations are made:

- For broken-rail–caused derailments, taking winter as a reference level, derailment frequencies given traffic exposure both in spring and summer are approximately 50% less likely than in winter (Table 5). Fall and winter have an insignificant difference in derailment rates given the same railroad and traffic volume. Regarding railroad differences, the two eastern railroads have relatively larger derailment frequencies given traffic exposure than the two western railroads due to broken rails. For example, derailment frequencies given traffic exposure on E1, E2 are three and two times of that on W1, respectively.
- For broken-wheel–caused derailments, taking winter as a reference level and given the same railroad and traffic volume, the other three seasons have relatively smaller derailment frequencies given traffic exposure. More specifically, derailment frequencies given traffic exposure in spring and fall are 73% and 51% of that in winter, and summer has an even lower derailment frequency given traffic exposure, just 37% of that in winter (Table 6). Regarding the railroad, two eastern railroads (E1 and E2) appear to have equal or lower frequencies of derailments given traffic exposure than western railroads (W1 and W2) due to broken wheels.
- For buckled-track–caused derailments, the derailment frequency given traffic exposure in summer is considerably large, 4 times of that spring and 10 times of that fall (Table 7). There was no buckled-track–caused derailment occurring in winter during the study period.

Table 6. COR of broken-wheel–caused derailment by season and railroad

Conditional odds ratio	12E Broken wheels
μ_{E1}/μ_{W2}	0.44 (0.28, 0.66)
μ_{E2}/μ_{W2}	1.04 (0.74, 1.43)
μ_{W1}/μ_{W2}	0.81 (0.62, 1.04)
$\mu_{\text{spring}}/\mu_{\text{winter}}$	0.73 (0.54, 0.95)
$\mu_{\text{summer}}/\mu_{\text{winter}}$	0.37 (0.25, 0.51)
$\mu_{\text{fall}}/\mu_{\text{winter}}$	0.51 (0.36, 0.68)

Note: The values in parentheses are the 95% confidence interval of COR.

Table 7. COR of buckled-track–caused derailment by season and railroad

Conditional odds ratio	05T Buckled track
μ_{E1}/μ_{W2}	0.69 (0.46, 1.01)
μ_{E2}/μ_{W2}	0.15 (0.05, 0.30)
μ_{W1}/μ_{W2}	0.55 (0.39, 0.75)
$\mu_{\text{spring}}/\mu_{\text{summer}}$	0.24 (0.16, 0.34)
$\mu_{\text{fall}}/\mu_{\text{summer}}$	0.10 (0.05, 0.16)

Note: The values in parentheses are the 95% confidence interval of COR.

Possible Explanations of Seasonal Effect on Studied Causes

Seasonal temperature changes may affect the dynamic behavior of the railroad components and have a significant effect on the infrastructure response (Salcher et al. 2016). Previous studies (Gonzales et al. 2013; Salcher et al. 2016) have shown a high impact of the surrounding air temperature on the structural stiffness based on long-term measurements. In their study, decreasing or increasing temperature leads to an increase or decrease of stiffness. The prior literature (Liu et al. 2013b; Zerbst et al. 2009) found that ambient temperature is related to the growth of broken rails. The thermal contraction forces in rails under lower temperatures will likely pull apart internal rail defects, causing more broken rails. A similar comparison of derailment rate by season in broken wheels demonstrates that summer has the lowest derailment rate, and winter has the highest broken-wheel–related derailment rate.

These statistical analysis results seem to be consistent with previous engineering and laboratory analyses, which showed that a decreased temperature can promote the appearance of fractures in rail stock or wheel material (Fuoco et al. 2004). In addition to the wheels' properties and performance, the interaction between track-related and rolling-stock–related defects was also identified (Liu et al. 2013a). For track buckling, no buckled-track–caused derailments occurred in winter in our studied data, which are Class I freight-train derailments on mainlines from 2000 to 2016, and summer has a significantly higher derailment rate than in other seasons. This finding can be explained via well-established buckling theories in the literature (Dobney et al. 2009, 2010; Kish and Samavedam 2013).

These explanations might also support the difference of freight-train derailments in eastern railroads and western railroads. The Western United States is mostly occupied by deserts and plateaus and is recorded as having higher temperatures than the Eastern United States in the warmer season (National Weather Service 2021). For example, the average temperatures recorded in Las Vegas and Dallas are even above 36°C in the summer season. In the colder season, the Eastern United States has lower temperatures than the Western United States in general. For example, the average temperatures of the center-east areas (e.g., Boston, Chicago) in January and February are below 0, which is lower than the average temperatures in most areas of the Western United States (e.g., west coast, desert, and plateaus). Overall, the temperature difference in the areas operated by the four freight railroads may have an impact on the variations of freight-train derailment frequency and rate. However, in previous studies and this research, there is a lack of further analysis or supportive findings regarding other seasonality-related variables, such as precipitation, humanity, and sunshine hours. These issues could be considered in future work depending on data availability.

Seasonality-Driven Freight-Train Derailment Risk Mitigation

Broken rails have been the leading cause of freight train derailments, leading to around \$500 million of damage costs in infrastructure and rolling stock since 2000 (FRA 2020). The mitigation of broken-rail–caused derailments is an increasingly critical field. Both visual inspection and track circuit can contribute to detecting broken rails at earlier stages and reducing the further adverse impact of the occurring broken rails. Therefore, although a broken rail has a greater likelihood to occur in the colder seasons due to tensile thermal stresses, this also improves the detectability of broken rails in winter months over summer months because the rail breaks and is pulled apart so it can be detected by track circuits (Dick 2001). Overall, the impact of lower temperature in colder seasons is not simply linear in broken rail–caused derailment occurrences, and currently existing detection technologies can also have unanticipated influences. The analytical results that derailment frequencies, given traffic exposure, in warmer seasons are approximately 50% less likely than those in winter seasons can be beneficial to optimize rail defect inspection frequency, accounting for the seasonal effects and occurrence of broken-rail–caused derailments.

The results of this analysis are useful for practitioners to quantitatively understand the difference of seasonal variation in derailment frequencies given traffic exposure. The identified seasonal impact is consistent with previous engineering studies in general, whereas the quantitative analytical results in this paper support an industry-level understanding of the seasonal impact on freight-train derailments, as well as the magnitude of the difference.

Furthermore, the methodology in this paper can be tailored to specific railroads (or regions) and provide a customized decision support to manage inspection and maintenance strategies given specific railroad or region, season, and traffic volume. The practitioners can use the method presented in this paper to analyze their own derailment data, accounting for a specific railroad, season, and traffic volume. Ultimately, we aim to provide the industry with a portfolio of data analysis techniques and tools for easily analyzing past derailment data, discovering useful information, and assisting with data-driven safety decisions.

Conclusions

This paper develops a novel application of the negative binomial regression model to identify and quantify the seasonal effect on US Class I freight railroad derailments, accounting for derailment cause, traffic exposure, and railroad. Three major derailment causes—broken rails, broken wheels, and buckled track—were analyzed statistically based on past derailments and traffic data. The results show the varying seasonal effects on derailment frequencies given traffic exposure by cause and railroad. Given traffic exposure and railroad, fall and winter double the broken-rail–caused derailment frequency given traffic exposure in comparison with spring and summer. Broken-wheel–caused derailments appear to occur less frequently in spring (27% less likely), summer (63% less likely), and fall (49% less likely) than in winter. There was no buckling in winter during the study period, whereas buckled-track–caused derailment frequency given traffic exposure in summer is 6 times of that in spring and 10 times of that in fall. These quantitative results can be beneficial to optimize inspection frequency of railroad infrastructure and rolling stock on a railroadwide basis. The statistical regression models developed in this paper can be adapted to other causes and other railroads.

The statistical analysis procedure can be used as a long-term reference for railway researchers to understand the relationship between derailment risks and influencing factors on various spatial and temporal scales. The results of this analysis are useful for practitioners to quantitatively understand the difference of seasonal variation in derailment frequencies given traffic exposure. The identified seasonal impact is consistent with previous engineering studies. At present, this research is developing a computer-aided decision support tool that can automate the statistical modeling process shown previously. Practitioners can use the tool to analyze derailment frequencies given traffic exposure for any specific railroad, season, and traffic volume. Moreover, although inspections and diagnostic measurements commonly employed in railroads are able to generate informative repair and corrective maintenance actions, each suffers from the limitations of workload and time schedule for restoration. Thus, in addition to providing the industry with a portfolio of data analysis techniques and tools for easily analyzing past derailment data, discovering useful information, and assisting with data-driven safety decisions, this paper ultimately supports an optimal allocation of train safety improvement resources.

Future Work

This study focuses on identifying the statistical distribution of railroad-specific derailment frequency by season, traffic volume, and other influencing factors. Due to data limitations, this paper was not able to perform a comprehensive analysis to explain the seasonal effect (particularly causal effect). As key explanatory variables in the seasonal effect, temperature and seasonal weather would be considered in future studies. Moreover, this paper fails to track the changes in derailment frequency given traffic exposure due to maintenance practices (such as wheel impact detectors, ultrasonic rail inspections, and vehicle track interaction systems) during the period analyzed in this study. One subsequent research direction is to extend this statistical methodology into collision and grade-crossing incidents, which are two common types of train accidents in the United States. In these two accident types, human errors are major causes. Apart from accident frequency, assessments of the severity of accidents such as the number of cars derailed, damage costs, and other measures of severity can be analyzed using similar statistical models.

Appendix. Empirical Mainline Derailment Rate by Derailment Cause and Railroad, 2000 to 2016

Railroad	Season	Number of derailments	Derailment rate per billion train-miles	Derailment rate per billion car-miles
E1	Spring	245	588	10.21
	Summer	234	586	10.17
	Fall	224	587	10.67
	Winter	277	760	12.59
E2	Spring	181	467	9.05
	Summer	159	432	8.37
	Fall	130	353	7.22
	Winter	193	554	10.16

Appendix. (*Continued.*)

Railroad	Season	Number of derailments	Derailment rate per billion train-miles	Derailment rate per billion car-miles
W1	Spring	452	652	8.69
	Summer	460	663	8.85
	Fall	417	601	8.51
	Winter	424	649	8.15
W2	Spring	417	564	9.07
	Summer	445	602	9.67
	Fall	374	495	8.50
	Winter	383	542	8.15

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

A large portion of the research was completed when the lead author was a graduate research assistant at Rutgers University. We thank Rutgers University for the support of this work.

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