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Research Article

Association between Truck Crashes due to Mechanical Failure and Truck Age

Jaeyoung Lee,[1] **Suyi Mao**,[1] **Mohamed Abdel-Aty**,[2] **Yanqi Lian**,[1] **Lishengsha Yue**,[2] **and Ilsoo Yun**[3]

[1]*School of Traffic and Transportation Engineering, Central South University, Changsha 410075, Hunan, China*
[2]*Department of Civil, Environmental, and Construction Engineering, University of Central Florida, Orlando, FL 32816, USA*
[3]*Department of Transportation System Engineering, Ajou University, Suwon 16499, Gyeonggi, Republic of Korea*

Correspondence should be addressed to Jaeyoung Lee; jaeyoung@knights.ucf.edu

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There have been efforts to restrict older trucks in many jurisdictions all over the world. The primary goal of the restrictions is to minimize greenhouse gas emissions. In addition to the environmental benefits, it is also possible that the truck age restriction could contribute to the enhancement of traffic safety. Older trucks are subject to longer travel-miles than newer trucks and tend to have higher mechanical failure rates. Extremely few studies have been done to explore the impact of trucks' age on their crash occurrence due to mechanical problems. This study aims to investigate the association between the truck crashes due to mechanical issues and the truck age. Two approaches are adopted to achieve the objective. First, a chi-square test reveals that the proportions of the mechanical failures among older trucks are higher than those among newer ones ($\chi^2 = 256.199$, $p < 0.0001$). Second, the modeling results indicate that the number of truck crashes due to mechanical failures is significantly increased by the truck age. The findings suggest that policies restricting older trucks should consider not only environmental effects but also traffic safety benefits.

1. Introduction

In the recent decades, a number of governments have started restricting older trucks on highways. The main goal of the restriction is to minimize environmental impacts from the older trucks. According to the California Air Resources Board (CARB), nearly all trucks and buses will be required to be equipped with 2010 or newer model year engines to reduce the particulate matter and oxides of nitrogen by January 1, 2023 [1]. Some governments encourage truck drivers to replace old trucks with new ones by providing incentives [2]. Incentive-based, voluntary vehicle replacement programs were found effective to reduce harmful air emissions by about 4%. Nevertheless, such voluntary programs are less effective compared to mandatory programs [3]. In addition, low emission zones (LEZs) programs restrict access by the most polluting vehicles. LEZs have been implemented in many cities worldwide, particularly in European Union countries [4]. Several studies have proven that LEZs are effective to decrease air pollutants' concentrations in urban areas by restricting old trucks [5, 6].

As shown above, policies and research studies related to the old truck restrictions have focused on the environmental impacts. In addition to the environmental benefits, the old truck ban policies might lead to the improvement of traffic safety. Extremely few studies have explored traffic safety of the old trucks. Conrad [7] asserted that older trucks are subject to longer travel-miles of wear than newer ones and eventually become unsafe, without a proper maintenance. Along with the wear, older trucks are less likely to be equipped with safety devices to prevent mechanical failures. In the United States, Antilock braking systems (ABS) have been mandated on tractors since 1997, and then ABS and air brakes have been required on semitrailers since 1998. Moreover, electronic stability control (ESC) was recently mandated for three-axle truck tractors manufactured after

2017 (49 CFR § 571). These mandatory safety devices for new trucks are expected to considerably reduce traffic crashes related to mechanical failure. In other words, older trucks without such equipment might be more exposed to danger. However, no study has examined the effect of truck's age on the number of traffic crashes occurring because of mechanical problem.

This study consists of two parts: (1) comparing the proportions of truck-involved crashes due to mechanical failure and truck-involved crashes due to nonmechanical issue and (2) estimating a crash prediction model to identify the effect of truck age on the number of crashes occurring due to mechanical failure. The rest of the paper is organized as follows. First, the data collection and processing procedure are described. Subsequently, the methodologies used in this analysis are explained, followed by the results and discussions. The final section summarizes and concludes the manuscript.

2. Data

In order to achieve the main objective of this study, data from two sources were collected and processed. The first data is obtained from the Fatality Analysis Reporting System (FARS) database, which is archived and managed by the US National Highway Traffic Safety Administration (NHTSA). The FARS is a nationwide census providing public yearly data regarding fatal injuries suffered in motor vehicle traffic crashes. The NHTSA archives data from 1975 to 2018. The data of truck-involved crashes that occurred between 2014 and 2018 were collected. Light trucks less than 10,000 lbs. GVWR (gross vehicle weight rating), such as pickup trucks and sport utility vehicles, were removed from the data. Overall, 21,726 truck-involved crashes occurred over the five years. The types of trucks and their counts are summarized in Table 1. As shown in the table, the most frequently observed type is truck-tractor (64.5%), and 25.6% are single-unit straight truck or Cab-Chassis (regardless of gross vehicle weight rating or GVWR).

Approximately 3.13% of the truck-involved crashes happened due to the mechanical failure of the trucks. Although the mechanical failure has a small proportion in the truck crashes, they are preventable with regular maintenance and management. Mechanical problem information was processed from the data file: contributing circumstances of the FARS. The contributing circumstances are defined as the vehicle's possible preexisting defects or maintenance conditions that may have contributed to the crash. The detailed mechanical problems and distribution are presented in Table 2. It is shown that tires and brake system are the majority of the mechanical problems (43.1% and 29.6%, respectively), followed by the problems of power train or exhaust system (6.0%).

The FARS provides the model year of the trucks that were involved in crashes. Based on the model year, truck age was calculated by subtracting the truck model year from the calendar year at the date of the crash. The distribution of the truck age is shown in Figure 1. About 62% of the trucks are less than ten years old, while 38% are ten years and older.

Furthermore, highway statistics of the Federal Highway Administration (FHWA) provides the number of registered trucks in the United States [8]. As of 2018, there were 152,701,631 registered trucks in the country. Nevertheless, the FHWA does not provide the registered trucks by age. Thus, the number of registered trucks by age was estimated using the "quasi-induced exposure" method. More details are provided in the Methodology section.

3. Methodology

As described in the Introduction, the current analysis has two parts. The first one is to compare the proportions of truck-involved crashes due to mechanical failure and nonfault (both not-at-fault driver and nonmechanical failure). The second one is to estimate a crash prediction model to identify the safety effects of truck age. For the first part, a chi-square test with the contingency table was conducted if the difference of the proportions is statistically significant. For the second part, a crash prediction model is developed for estimating the effects of truck age on safety. From the modeling result, a crash modification factor (CMF) that shows the safety effects of truck aging is estimated.

A Poisson model has been widely used for crash frequency modeling; however, it is unsuitable if the data is overdispersed. A negative binomial model is an alternative to Poisson model, which overcomes possible overdispersion in the data. A negative binomial model is specified as follows [9]:

$$y_i \sim \text{Poisson}(\lambda_i), \tag{1}$$

$$\lambda_i = \exp\left(\beta_0 + \sum \beta X_i + \varepsilon_i\right), \tag{2}$$

where y_i is the observed number of truck crashes occurring due to mechanical failure for each truck age i, λ_i is the Poisson mean of y_i, β_0 is the intercept term, β_s are the coefficient estimates of model covariates X_i, and $\exp(\varepsilon_i)$ is a gamma-distributed error component with mean 1 and variance α. The relationship between the variances from the mean in the negative binomial model is as follows:

$$\text{VAR}(y_i) = E(y_i)\left[\left(1 + \alpha E(y_i)\right)\right]. \tag{3}$$

The parameter α is referred to as the overdispersion parameter. If the overdispersion parameter is zero, the negative binomial converges to a Poisson model. In other words, the crash data is not dispersed (i.e., $\text{VAR}(y_i) = E(y_i)$).

A CMF from the estimated model is calculated by exponentiating the coefficient of the variable of interest (i.e., truck age) [10–12]. Along with other count modeling approaches for crashes, an exposure variable is required in the modeling estimation. Nevertheless, the number of trucks by each truck age is not obtainable. For this reason, a quasi-induced exposure method is employed to estimate the number of trucks by age.

Table 1: Truck types and distribution.

Truck type	Count	Percentage
Truck-tractor (cab only, or with any number of trailing unit)	14,015	64.51
Single-unit straight truck or cab-chassis (26,000 lbs + GVWR)	3,024	13.92
Single-unit straight truck or cab-chassis (19,500–26,000 lbs. GVWR)	1,167	5.37
Single-unit straight truck or cab-chassis (10,000–19,500 lbs. GVWR)	1,364	6.28
Medium/heavy pickup (10,000 lbs. + GVWR)	1,265	5.82
Single-unit straight truck or cab-chassis (GVWR unknown)	439	2.02
Unknown medium/heavy truck type	89	0.41
Camper or motorhome, unknown truck type	85	0.39
Medium/heavy truck based motorhome	120	0.55
Step van (10,000 lbs. GVWR)	74	0.34
Unknown if single unit or combination medium truck heavy truck (26,000 lbs. + GVWR)	47	0.22
Unknown if single unit or combination medium truck (10,000–26,000 lbs. GVWR)	28	0.13
Unknown truck type (light/medium/heavy)	9	0.04
Total	21,726	100.00

3.1. Quasi-Induced Exposure Approach. The quasi-induced exposure method is applied to estimate the increase of being involved in a crash associated with driver-related or vehicle-related characteristics when there is no direct way to measure the intensity of exposure of the characteristics [13]. The basic idea of the quasi-induced method is that nonfault vehicles (e.g., no mechanical failure, no violation, and no alcohol/drugs) involved in traffic crashes are an approximately random sample of the vehicle population [12–15].

Some might be concerned of assuming that non-at-fault trucks are a random sample of trucks because, in fatal multivehicle crashes involving a truck, the truck driver is likely to survive and provide a narrative that might blame that the truck had mechanical faults. Thus, in this study, "nonfault trucks" include not only not-at-fault drivers' trucks (e.g., with a traffic violation), but also nonmechanical failure trucks. In this paper, the percentage of trucks of each age in nonfault trucks is estimated using this assumption. The number of trucks for each age is calculated by multiplying the percentage of each age and the total number of registered trucks (as of 2018) from the FHWA statistics [8].

$$\text{Truck}_i = \left(\frac{NFT_i}{\sum_{i=0} NFT_i}\right) \times \text{Total Trucks}, \tag{4}$$

where Truck_i is the number of trucks for age i, NFT_i is the number of nonfault trucks in crashes for age i, and Total Trucks is the total number of registered trucks.

4. Results

For the first analysis, a chi-square test with the contingency table was conducted to check if there is a significant difference between the proportions of truck-involved crashes due to mechanical failure and nonmechanical failure by four age groups (i.e., 0–9, 10–19, 20–29, and 30–40 years old). Table 3 presents the contingency table and the chi-square test result.

The contingency table shows that only 2.0% of the truck-involved crashes occurred due to mechanical failure for the trucks aged 0–9 years. On the other hand, the percentages went up to 4.7% to 8.6% for the trucks 10–19 years and 20–29 years old, respectively. The percentage is the highest among the trucks aged 30–40 years (13.7%). The chi-square test ($\chi^2 = 256.19906$, $p < 0.0001$) confirmed that the proportions are significantly different by the age group.

For the second analysis, the number of trucks for each age was estimated using the quasi-induced exposure method before developing the crash model (Table 4).

Using the estimated trucks by age and the crash data, the rates of mechanical failures per estimated trucks can be calculated (Table 5). The mechanical failure rate of 0–9 years is 2.657, and that of 10–19 years is 6.329. When the truck age is between 20 and 29 years, the crash rate went up to 12.075. The highest crash rate is observed in the age 30–40 years old group, which is 20.299. The crash rates indicate that the older trucks are more likely to have mechanical problems.

In the modeling process, the authors firstly attempted a negative binomial model; however, the overdispersion parameter was quite small ($\alpha = 0.068$). Thus, a Poisson model was developed and compared with the negative binomial model using likelihood ratio test. The test indicates no significant difference between the two models' performance ($\chi^2 = 0.7$, $df = 1$, $p = 0.403$). Also, the AIC of the Poisson model (229.5) was slightly smaller than that of the negative binomial model (230.8). Therefore, the Poisson model was chosen as the final model in this study.

The Poisson modeling results are summarized in Table 6. The model was estimated for the number of truck crashes occurring due to the mechanical failure. The estimated exposure variable: the natural logarithm of estimated trucks well explains the variations in the mechanical failure truck-involved crash data. The truck age variable has a significant positive association with the number of truck's mechanical failure.

5. Discussion of the Results

The most important finding from the analysis is that older trucks are more likely to cause a crash due to mechanical failure. From the coefficient and the standard deviation, a CMF and its 95% confidence interval were estimated (Table 7). The estimated CMF for one-year age increase is 1.10409, which suggests that an older truck is 10.41% more

Table 2: Mechanical problems and distributions.

Mechanical problem	Count	Percentage
Tires	293	43.1
Brake system	201	29.6
Power train or exhaust system	41	6.0
Combination of two or more problems	25	3.7
Head, signal, or other light	32	4.7
Truck coupling/trailer hitch/safety chains	20	2.9
Wheels	9	1.3
Suspension	7	1.0
Steering	9	1.3
Body, doors	5	0.7
Safety systems	4	0.6
Wipers/windows/windshield	2	0.3
Vehicle contributing factors-no details	32	4.7
Total	680	100.0

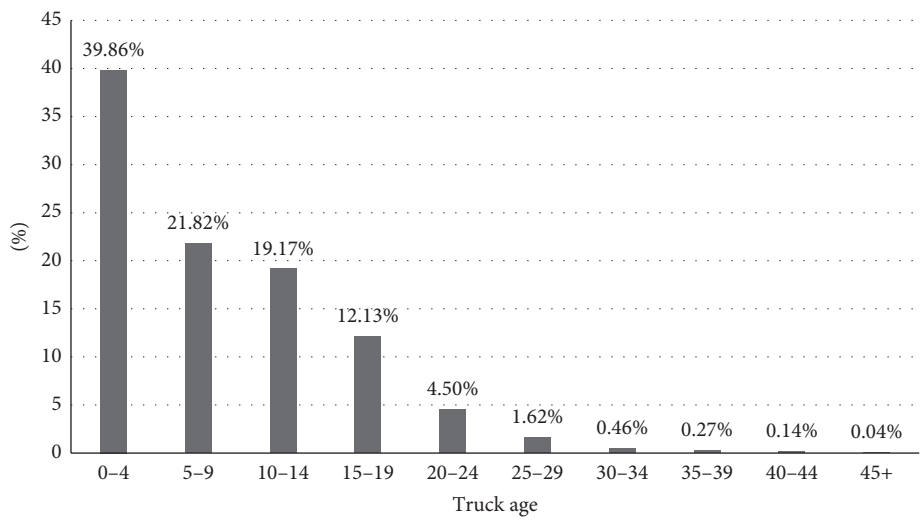

Figure 1: Distribution of truck age.

Table 3: Chi-square test with the contingency table.

Classification	0–9 years	10–19 years	20–29 years	30–40 years	Sum
Nonfault	12,245	6,008	1,099	132	19,484
Mechanical failures	255	298	104	21	678
Sum	12,500	6,306	1,203	153	20,162
Percentage of the mechanical failures	2.0%	4.7%	8.6%	13.7%	3.4%
Chi-square test			256.19906 ($p < 0.0001$)		

likely to have a mechanical failure. The 95% confidence interval of the CMF indicates the probability to face a mechanical failure for an older truck by one year is increased by 7.39%–13.51%.

Figure 2 describes the relationship between the rate of mechanical failure (multiplied by million) and the truck age. The predicted rates are quite accurate when the truck age is younger than 20 years old, while the errors are larger after 20 years old. It is because the number of mechanical failures for the trucks younger than 20 years old is sufficient, whereas the number for trucks older than 20 years old is extremely small, particularly after 30 years old. The small number of mechanical failures resulted in large fluctuations in the older trucks (see Table 4).

Table 4: Estimated trucks from the quasi-induced exposure method.

Age	No. of nonfault trucks	% of nonfault trucks	Estimated number of trucks	Mechanical failures
0	2265	11.62	17,751,447	22
1	1778	9.13	13,934,690	17
2	1616	8.29	12,665,050	35
3	1251	6.42	9,804,442	15
4	1040	5.34	8,150,775	25
5	798	4.10	6,254,152	26
6	751	3.85	5,885,800	15
7	847	4.35	6,638,179	37
8	922	4.73	7,225,975	32
9	977	5.01	7,657,026	31
10	957	4.91	7,500,280	40
11	923	4.74	7,233,813	37
12	699	3.59	5,478,261	28
13	566	2.90	4,435,902	21
14	550	2.82	4,310,506	30
15	583	2.99	4,569,136	28
16	514	2.64	4,028,364	28
17	483	2.48	3,785,408	32
18	421	2.16	3,299,496	30
19	312	1.60	2,445,232	24
20	248	1.27	1,943,646	26
21	202	1.04	1,583,131	13
22	148	0.76	1,159,918	6
23	124	0.64	971,823	10
24	93	0.48	728,867	7
25	73	0.37	572,122	10
26	56	0.29	438,888	9
27	63	0.32	493,749	8
28	43	0.22	337,003	6
29	49	0.25	384,027	9
30	24	0.12	188,095	4
31	28	0.14	219,444	2
32	8	0.04	62,698	0
33	12	0.06	94,047	2
34	7	0.04	54,861	3
35	9	0.05	70,536	0
36	8	0.04	62,698	2
37	9	0.05	70,536	3
38	13	0.07	101,885	3
39	5	0.03	39,186	1
40	9	0.05	70,536	1
Sum	19,484	100.0	152,701,631	678

Table 5: Rates of truck-involved crashes occurring due to mechanical failure.

Age group	No. of mechanical failures	Estimated number of trucks	Mechanical failure rates per million trucks
0–9 years	255	95,967,536	2.65715
10–19 years	298	47,086,399	6.32879
20–29 years	104	8,613,175	12.07453
30–40 years	21	1,034,521	20.29924
Sum	678	152,701,631	4.44003

Table 6: Poisson model for truck crashes occurring due to mechanical failure by truck age ($N = 41$).

Variable	Coefficient	Standard error	p
Intercept	−15.8256***	1.77368	<0.0001
Log (estimated number of trucks)	1.16042***	0.10521	<0.0001
Truck age	0.09902***	0.01413	<0.0001
Goodness-of-Fit	Statistic	Equation	
Log-likelihood (full)	−111.37728	—	
Log-likelihood (null)	−310.88424	—	
McFadden's R^2	0.64059	$1 - (LL(\text{full})/LL(\text{null}))$	
MAE (median absolute error)	3.41879	$\frac{1}{n}\sum_{i=1}^{N}\lvert y_i - \hat{y}_i\rvert$	
RMSE (root mean squared error)	4.93716	$\sqrt{\frac{1}{n}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$	
MAPE (mean absolute percentage error)	0.20674	$\sum_{i=1}^{N}\lvert y_i - \hat{y}_i\rvert / \sum_{i=1}^{N}\lvert y_i\rvert$	

y_i is the observed crash count at truck age i, and $\hat{y}_i$ is the predicted crash count at truck age i. ***Significant at 99% confidence level.

Table 7: Crash modification function of truck age for truck crashes occurring due to mechanical failure.

Factor	CMF	95% confidence interval	
		Lower limit	Upper limit
Truck age	1.10409	1.07392	1.13510

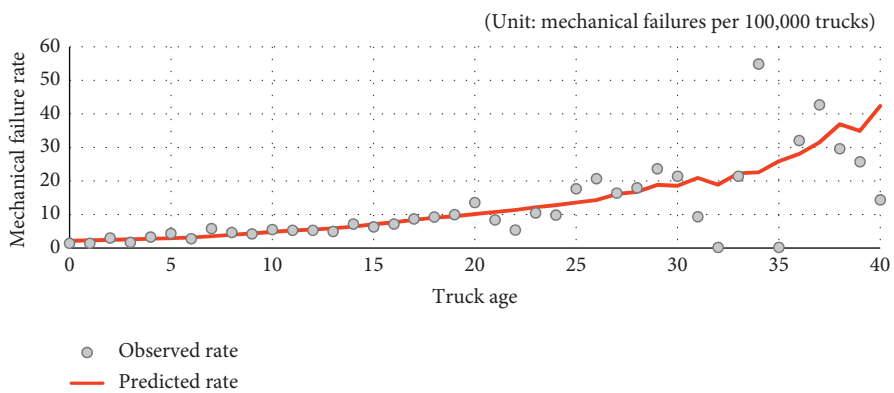

Figure 2: Mechanical failure crash rate by truck age.

6. Summary and Conclusions

The study investigated the relationship between the number of truck crashes due to mechanical failure and truck age. The first analysis compared the proportion of mechanical failure crashes by age group. The result showed that only 2.0% of the truck-involved crashes occurred due to mechanical failure for the trucks aged 0–9 years. On the other hand, the percentages went up to 4.7% and 8.6% for 10–19 years and 20–29 years old trucks, respectively. The percentage is the highest among the trucks aged 30–40 years (13.7%). The chi-square test indicated that the difference in the proportions is statistically significant. In the second analysis, a Poisson model was developed to find the association between the number of mechanical failure truck crashes and truck age. The modeling results identified that the probability of crash occurrence due to mechanical failure is increased by 10.41% for a one-year older truck. From those findings, it is concluded that the number of truck crashes involving mechanical failure is significantly increased by truck age.

In the latest decade, old truck restriction policies have been initiated in many jurisdictions. For example, California will require all trucks to have 2010 model year engines or newer by 2023 [1]. Such policies mainly focus to reduce air pollution. However, it is strongly recommended that policy makers consider restricting older trucks with more diverse aspects. Even in areas without serious air pollution, the old truck restrictions should be considered from the viewpoint of traffic safety. The results from this study can be supporting such policies in the safety aspects as it was shown that trucks older than 10 years are significantly likely to have mechanical failures. Also, not only restriction, but also providing incentives would be effective to encourage truck owners to replace their old trucks with new ones. If such restrictions or incentive programs are difficult to be immediately employed, proper and frequent maintenance and stricter mandatory inspections for old trucks would be required. Moreover, truck manufacturers can understand the relationship between age and mechanical failure from the findings from this study, and they

might want to review their maintenance checklist by truck age for drivers, which might be helpful to prevent mechanical failure truck crashes.

Currently, it is hard to think that old trucks have intelligent connected vehicles (ICV) equipment. However, in the future, old trucks at that time will be probably equipped with ICV devices. If this is the case, real-time safety assessment will be available, and when a higher risk is anticipated due to the mechanical failure in specific situations (e.g., poor pavement condition with relatively old tire, slippery surface with dated steering), adjacent connected vehicles will be warned to keep a sufficient distance from the truck (V2V). If a truck is identified with a higher risk of mechanical failure, and the current traffic/road environment is dangerous, the infrastructure will be able to send an advisory message (e.g., slow down) to the truck (I2V) [16, 17]. These types of proactive ICV countermeasures might decrease the number of crashes due to truck's mechanical failure.

Although this study identified key findings, it is not without limitations. Those limitations should be addressed in follow-up studies. First, the estimated number of trucks by age was included in the model using the quasi-induced exposure method. It is necessary to validate whether the estimated trucks are accurate and reliable. Second, the data used in this study was collected from the FARS, which only provides crashes involving a fatality. Since a fatal crash has a tendency to be investigated with a reliance on narratives of survivors in the absence of other evidence, the recorded contributing factors might not be very trustworthy. For these reasons, it is possible that the results are biased. Lastly, the study was conducted only using crash data. The findings from this study would be more reliable if the results are substantiated by actual truck inspections.

Data Availability

The data are available from Fatality Analysis Reporting System (FARS).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Study conception and design were conducted by Jaeyoung Lee, Mohamed Abdel-Aty, and Ilsoo Yun; data collection was carried out by Jaeyoung Lee; analysis and interpretation of results were carried out by Jaeyoung Lee, Suyi Mao, Mohamed Abdel-Aty, Yanqi Lian, and Lishengsha Yue; draft manuscript preparation was carried out by Jaeyoung Lee, Suyi Mao, Yanqi Lian, and Lishengsha Yue. All authors reviewed the results and approved the final version of the manuscript.

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