

Mechanical condition of vehicles and the durability of road safety systems: A 17-year time-series analysis in Benin (2007–2023)

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Abstract: *Objective.* This study analyses the relationship between vehicle mechanical condition and the frequency of road accidents in Benin over seventeen years, testing whether vehicles in poor condition are disproportionately involved in accidents and whether this relationship remains stable over time, to inform sustainable road safety policies in a resource-constrained context. *Methodology.* Using national monthly accident data from 2007 to 2023 (204 observations, covering 88,605 accidents, 153,531 vehicles in good condition and 3,957 vehicles in poor condition), the study employs descriptive statistics, paired Wilcoxon tests, Pearson's correlation analysis, multiple linear regression and Poisson regression modelling (GLM), supplemented by interaction and structural break analysis to assess temporal stability. We conducted robustness analyses using a quasi-Poisson model with Newey-West robust standard errors (lag = 12) to correct for autocorrelation and underdispersion. We performed a Granger causality test to assess the direction of causality. *Results.* The Poisson regression shows that each additional vehicle in poor condition increases the number of monthly accidents by 0.15 per cent (IRR = 1.0015; 95% CI [1.0005 – 1.0025]; $p = 0.002$), a modest but statistically significant and temporally stable effect (interaction $p = 0.649$). Robustness analyses using Newey-West standard errors confirm this effect ($z = 5.933$; $p < 0.001$). A negative aggregate correlation between the proportion of vehicles in poor condition and the total number of accidents ($r = -0.308$) suggests confounding by inspection cycles or economic conditions rather than a genuine protective effect. The Granger causality test indicates that vehicles in poor condition statistically predict future changes in the number of accidents ($F = 3.27$; $p = 0.022$), alleviating concerns about reverse causality. A policy impact simulation estimates that a 10 per cent reduction in vehicles in poor condition would prevent approximately 15 accidents per year. *Theoretical contribution.*

This paper offers one of the few long-term, monthly-resolution analyses of the relationship between vehicle condition and accident frequency from a sub-Saharan African country. It is among the first to formally test the temporal stability of this relationship. *Practical implications.* The results support sustained investment in periodic vehicle inspections, incentives for maintenance and targeted roadside checks as part of Benin's contribution to the United Nations Decade of Action for Road Safety and SDG 3.6, whilst emphasising that vehicle condition accounts for only a modest proportion of the variance in accidents compared with exposure and infrastructure factors.

Keywords: mechanical condition of vehicles, road accidents, Poisson regression, vehicle inspection, road safety, Benin, time series, Granger causality

Sustainable Development Goals (SDGs): **SDG 3:** Good health and well-being; **SDG 9:** Industry, innovation and infrastructure; **SDG 11:** Sustainable cities and communities

1. Introduction

Road traffic accidents constitute a global health crisis, killing approximately 1.3 million people a year and injuring a further 25 to 50 million, with a disproportionate burden in low-income countries, which account for 90 per cent of deaths despite owning only 54 per cent of the world's vehicles (WHO, 2007). The mortality rate from road traffic crashes stands at 18.2 per 100,000 population worldwide, with Africa recording the highest regional rate at 26.6 deaths per 100,000 population (WHO, 2018). Road traffic crashes remain the leading cause of death among children and young people aged 5 to 29, and more than half of these deaths involve pedestrians, cyclists and motorcyclists, particularly those living in low- and middle-income countries (WHO, 2023).

This study falls squarely within the framework of Sustainable Development Goal (SDG) 3.6, which aims to halve deaths and injuries from road traffic crashes by 2030, as well as the Decade of Action for Road Safety (2021–2030). Improving the mechanical condition of the vehicle fleet is a sustainable measure that not only enhances road safety but also reduces emissions and extends vehicle lifespans, aligning with the broader mission of sustainable transport.

In developing countries, this issue is particularly acute because of rapid growth in the number of vehicles on the roads, the ageing of vehicles in circulation, and often inadequate maintenance standards. While human factors are widely recognised as the main cause of road traffic accidents, technical faults in vehicles remain a growing concern for road safety authorities. The mechanical condition of vehicles encompasses all systems that ensure proper functioning and safety: brakes, tyres, steering, lighting, suspension, and electrical systems. Deterioration of these components, resulting from inadequate maintenance, the use of non-compliant spare parts, or simply ageing, can seriously compromise the driver's ability to control the vehicle and react effectively in emergencies.

In Benin, the growing number of vehicles on the roads, the ageing vehicle fleet, and structural constraints in maintenance and roadworthiness testing are contributing to a rise in collisions and road accidents. Despite the construction of new and safer roads, the number of collisions continues to rise, with more than three thousand recorded each year.

In a context where human factors account for the majority of accidents, what proportion is actually attributable to mechanical faults? Do vehicles in poor condition really constitute a group at significantly higher risk than well-maintained vehicles? Is this over-representation, if it exists, constant over time, or does it vary according to contextual factors such as the seasons, traffic volume or weather conditions?

This study addresses the following central question: To what extent does a vehicle's general condition influence the frequency of road accidents, and is this influence stable over time? This main question is broken down into two specific sub-questions:

1. Are vehicles in poor condition significantly more likely to be involved in accidents than those in good condition?
2. Does the difference between the two categories remain constant over time, or does it vary by period?

The overall objective of this study is to analyse the impact of a vehicle's condition (good versus poor) on the frequency of road accidents. More specifically, the study will: (1) compare the number of accidents involving vehicles in good condition with those in poor condition to determine whether either category is statistically over-represented; and (2) examine monthly trends in accidents according to vehicle condition in order to identify any temporal variations in the relationship between mechanical condition and the occurrence of accidents.

2. Literature review

2.1. General technical condition of the vehicle and its role in accidents

Viewing the vehicle as a dynamic system comprising interdependent mechanical components, Hoque and Hasan (2007) point out that technical faults, particularly in the braking, steering and lighting systems or with the tyres, directly compromise the vehicle's operational safety on the road. They estimate that between 2 and 8.5 per cent of accidents in developed countries are attributable to technically defective vehicles, a proportion that is substantially higher on road networks with less rigorous maintenance standards. Similarly, Gothie (2026) confirms that a vehicle's intrinsic characteristics, mechanical performance, and maintenance level determine its ability to maintain a safe trajectory and respond to emergency manoeuvres.

Several empirical studies corroborate this finding by highlighting the direct impact of mechanical faults and physical configurations on accident rates, even in very different road contexts. In China, Yan et al. (2021) demonstrate, based on an analysis of major accidents involving commercial vehicles, that mechanical failures are one of the predominant direct material causes. In the same country, Liu et al. (2018), using a sample of 346 extremely serious accidents, identified the type of heavy goods vehicle and structural overloading as major predictors of accidents. Further south, in Nigeria, Odelowo (1993) established a direct correlation between the presence of articulated lorries in an advanced state of physical deterioration (road wrecks) and high rates of fatal accidents. The convergence of these findings, from different vehicle fleets and regulatory contexts, reinforces the strength of the link between a vehicle's physical deterioration and accident severity.

2.2. Tyres: a critical point of contact with the road

As the sole point of contact between the vehicle and the road surface, tyres are the mechanical component most directly associated with the loss of dynamic control. Gorzelańczyk et al. (2023), drawing on data from roadworthiness tests in Poland, reveal that tyres, together with the steering system, have the highest defect rate (40 per cent). Das et al. (2021) confirm that advanced tread wear is among the predominant material defects recorded in serious accidents in Louisiana. Serre et al. (2019), drawing on detailed assessments of light commercial vehicles, show that the technical non-conformities identified relate almost exclusively to incorrect tyre pressure or exceeding the load index.

The impact of tyre failures on vehicle trajectory is well documented. In Pakistan, sudden tyre blowouts have been identified as the direct material cause of 11.7 per cent of accidents recorded on the M-2 motorway (Iqbal, 2020). In a different road context, Haq et al. (2020), using Bayesian logistic modelling applied to ten years' worth of data from Wyoming, highlight the increased vulnerability of commercial vehicles and their suspension systems when subjected to rolling stresses on rough surfaces, justifying strict regulatory monitoring of tread depth. In terms of vehicle physics, Kowalski (2026a) demonstrates through numerical simulation that any alteration or deterioration in the tyre's structure irreversibly degrades lateral stability, resulting in a physical inability to maintain the intended trajectory.

2.3. The braking system and electronic dynamic control systems

The braking system is the most critical active safety component for regulating the vehicle's kinetic energy; however, this functional criticality must not be confused with the frequency of defects observed during roadworthiness tests, where tyres and steering show the highest non-compliance rate (see section 2). In a systematic review of twenty-five epidemiological studies, Robb et al. (2008) identified a significant increase in the risk of accidents resulting in personal injury for road trains (tractor-trailer combinations) with braking faults. Iqbal (2020) attributes 7.4 per cent of the overall accident rate on the M-2 motorway to direct braking system failures. Using a hybrid multi-criteria evaluation method combining DEMATEL and ANP, Ganji et al. (2018) rank the braking system as the most important criterion for the vehicle's mechanical safety, ahead of fuel systems and electrical circuits. Similarly, Agebure et al. (2023) rank braking faults, tyre wear and lighting failures as the leading mechanical causes of accidents. In Ecuador, Montero-Salgado et al. (2022) identify an imbalance in braking forces between the wheels on the same axle and ineffective parking brakes as recurring faults. Simović et al. (2025) quantify this contribution: of all technical causes recorded in their sample, braking system failures account for 17.4 per cent, corresponding to approximately 15 per cent of all accidents attributable to technical faults.

The integration of electronic traction control systems also alters the vehicle's dynamic response. Gądek-Hawlena and Jac (2026) analyse the behaviour of anti-skid systems (ASR) and speed control devices on heavy goods vehicles, demonstrating that the proper mechanical functioning of these systems helps prevent a loss of traction during phases of high engine torque demand. Finally, Kowalski (2026b) uses simulation to model the impact of mechanical failure in the braking system: the inability to dissipate speed increases impact speed, leading to a massive increase in energy transfer and structural deformation of the front bodywork of up to 0.6 metres.

2.4. Steering, lighting and associated components

Steering mechanisms and lighting systems are essential to a vehicle's manoeuvrability and passive signalling. Gorzelańczyk et al. (2023) highlight that the steering system, like tyres, has the highest rate of technical non-compliance (40 per cent) during periodic inspections. Robb et al. (2008) confirm the aggravating role of excessive play or broken steering links in accidents involving heavy goods vehicles. Regarding lighting and active visibility, Montero-Salgado et al. (2022) identify misalignment or headlamp failure as one of the most common mechanical faults on the road.

Failures in other mechanical subsystems can also compromise overall vehicle safety by triggering thermal incidents. Ren et al. (2019), in a statistical analysis of fires occurring in road tunnels in China (2000–2016), demonstrate that over 50 per cent of fires are the result of technical malfunctions (mechanical overheating, electrical short circuits, leaks of flammable fluids), with heavy goods vehicles accounting for 58.2 per cent of the vehicles involved.

2.5. Maintenance, quality of parts and ageing of the vehicle fleet

The cumulative wear and tear of mechanical components is directly linked to vehicle age and the maintenance practices applied to the fleet. Das et al. (2021), using a Bayesian approach, establish a positive correlation between vehicle age and increased severity of material damage in a crash. Qu et al. (2019), using the GA-XGBoost algorithm, ranked vehicle age among the seven most predictive physical variables for accident occurrence. Hudec et al. (2022) observed a linear decline in roadworthiness with vehicle age in the Slovak Republic, with the number of faults per component increasing as vehicles age. Kurniawan et al. (2026) empirically confirm this finding in Indonesia (Bantul), showing that the age of light commercial vehicles directly determines the failure rate in roadworthiness tests due to structural and mechanical fatigue of components. Siddique (2018), in Bangladesh, shows, using an ordered Probit model, that the accumulation of multiple uncorrected mechanical faults on a single vehicle significantly increases accident severity.

Beyond age, spare-part quality and the presence of safety features are major mechanical determinants. Serre et al. (2019) found that vehicles manufactured before 2012 have a material deficiency in active and passive safety systems compared with more recent models, increasing their

intrinsic vulnerability. Agbo et al. (2018) highlight the impact of reconditioned or used components: their study of 880 mechanics shows a direct correlation between the fitting of worn second-hand parts and the occurrence of mechanical failures ($R^2 = 0.46$), as well as with the frequency of accidents attributable to component failure ($R^2 = 0.65$). Finally, Rešetar et al. (2018) highlight the effect of vehicle taxation policies in Croatia, which, by slowing down the renewal of the vehicle fleet, encourage the continued use of technically obsolete and worn-out vehicles, thereby increasing the overall rate of mechanical failure.

2.6. Periodic roadworthiness testing and fault detection technologies

Periodic roadworthiness testing is the regulatory mechanism designed to assess the mechanical fitness of vehicles. Zovak et al. (2016) establish that in Croatia more than 22 per cent of vehicles on the road have major non-compliances and that statistical records underestimate the actual proportion of mechanical faults in accidents. Cuerden et al. (2011), in the United Kingdom, modelled the impact of extending the intervals between roadworthiness tests (MOT tests) and concluded that reducing frequency would directly increase undetected mechanical faults and the associated accident rate. Das et al. (2019) highlight that, in the United States, 2.6 per cent of fatal accidents result from manufacturing defects or faults, emphasising the need for mandatory inspections. However, the preventive impact of vehicle inspections is the subject of mixed findings: Jarosiński (2014) finds no direct statistical correlation between the introduction of periodic inspections in Poland and a reduction in the number of fatal accidents, whilst Martín-delosReyes et al. (2021), in a systematic review of six rigorous studies, observe a moderate reduction in accidents without establishing an exclusive causal relationship, as effectiveness depends on the rigour of the technical inspection criteria.

Given the limitations of one-off periodic inspections, on-board diagnostic and early-detection technologies offer new prospects for predictive maintenance. Hossain et al. (2024) summarise the contribution of artificial intelligence algorithms applied to sensor data streams to predict wear or imminent failure in mechanical sub-assemblies. Complementarily, Suman et al. (2022) have developed a system for detecting mechanical anomalies based on acoustic signal processing (Kalman filter and MFCC coefficients), enabling the identification of a material defect before the component fails.

2.7. Measurement and quantification of the mechanical contribution to accident rates

The quantitative assessment of the proportion of accidents attributable to technical faults varies depending on the assessment methodologies used and the specific characteristics of national vehicle fleets. The table below summarises the contribution rates of vehicle faults and mechanical components identified in the literature:

Table 1: Contribution rates of vehicle faults and mechanical components identified in the literature

Author(s) and year	Country / Context	Component / Factor studied	Proportion / Measured impact
Hoque & Hasan (2007)	Developed countries	Overall technical condition of the vehicle	2.0% to 8.5% of accidents (developed countries)
Das et al. (2021)	United States (Louisiana)	Overall mechanical faults	2.0 per cent of accidents
Das et al. (2018)	United States	Manufacturing defects	6.35 per cent of fatal accidents
Singh et al. (2016)	India	Vehicle mechanical faults	8.4 per cent of fatal accidents
Shen et al. (2014)	China	Technical faults (tankers)	19.6% of accidents involving hazardous materials
Iqbal (2020)	Pakistan (M-2 motorway)	General vehicle-related factors - Tyre blowout - Brake system failure	25.6 per cent of all accidents - 11.7 per cent of accidents - 7.4 per cent of accidents
Amo (2014)	Ghana	No vehicle fault	87.46 per cent of accidents not related to observed faults
Simović et al. (2025)	General / Modelling	Brake failure	15.0 per cent of technical accidents (17.4 per cent of technical causes)
Gorzelańczyk et al. (2023)	Poland	Roadworthiness test: Tyres and steering	40.0% of faults found on vehicles

Source: the author, based on the literature

A comparative analysis of these data reveals marked heterogeneity, which can be explained by differences in the definitions used in the investigations (confirmed vs suspected faults) and by the average level of fleet maintenance. This heterogeneity is also due to the nature of the indicators used, which are not strictly comparable with one another: some studies (Hoque & Hasan, Iqbal, Simović et al.) measure the proportion of accidents directly attributable to a mechanical fault, whilst others (Zovak et al., Gorzelańczyk et al.) measure a non-compliance rate identified during roadworthiness tests, with no direct link established to accident rates. Methodologically, the frequent underestimation of mechanical factors may reflect the complexity of post-collision assessments, where structural deformation often masks prior component failure. Nevertheless, the reported figures confirm that a vehicle's deteriorating mechanical condition is a major explanatory variable for road accidents.

One finding deserves particular attention: the study by Amo (2014) in Ghana, which is the only one to indicate that 87.46 per cent of accidents are not associated with any apparent vehicle fault, stands in direct contrast to the trend observed in the other eight studies in the table. This discrepancy likely reflects methodological differences rather than a genuine absence of mechanical causality: the study relies on records of defects visible at the time of the accident, without in-depth technical assessment, whereas most other studies rely on detailed post-collision inspections that can reveal non-apparent faults. This contrast suggests that the main hypothesis should be qualified by the level of methodological rigour of the expert assessments used, rather than affirmed across the board.

Research hypothesis

Following this review, which has refocused on the material dimension, the general working hypothesis is as follows: the mechanical and technical condition of the vehicle (tyre wear, brake failure, obsolescence, and maintenance defects) significantly influences the occurrence and severity of road traffic accidents.

This hypothesis is broken down into two specific hypotheses:

H1: Vehicles in poor condition constitute a significant monthly contributing factor to road traffic accidents, all other things being equal.

H2: This over-representation of vehicles in poor condition in accidents is consistently observable over several consecutive months, indicating a stable relationship that is not cyclical.

3. Research methods

3.1. Data

The analysis is based on a sample covering 204 months (2007–2023) comprising 41 variables relating to road traffic accidents in Benin. The data were checked for completeness: no missing values were detected in the entire dataset.

3.2. Variables

The dependent variable is the number of monthly accidents. The main independent variables are: (a) vehicles in good condition involved in accidents, (b) vehicles in poor condition involved in accidents, and (c) the proportion of vehicles in poor condition. Control variables include weather conditions (rain), area (urban/rural), road surface condition, night-time lighting and load volume.

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3.3. Statistical methods

The following statistical methods were employed: (1) descriptive statistics and normality tests (Shapiro-Wilk); (2) the paired Wilcoxon test to compare distributions; (3) Pearson's correlation analysis; (4) multiple linear regression; (5) Poisson regression modelling (GLM); (6) Quasi-Poisson modelling with Newey-West robust standard errors to correct for autocorrelation and underdispersion; (7) Granger causality test to assess the direction of causality; (8) time series decomposition (STL); (9) stationarity tests (augmented Dickey–Fuller); and (10) ANOVA analysis for inter-period comparisons.

4. Research findings

4.1. Descriptive statistics

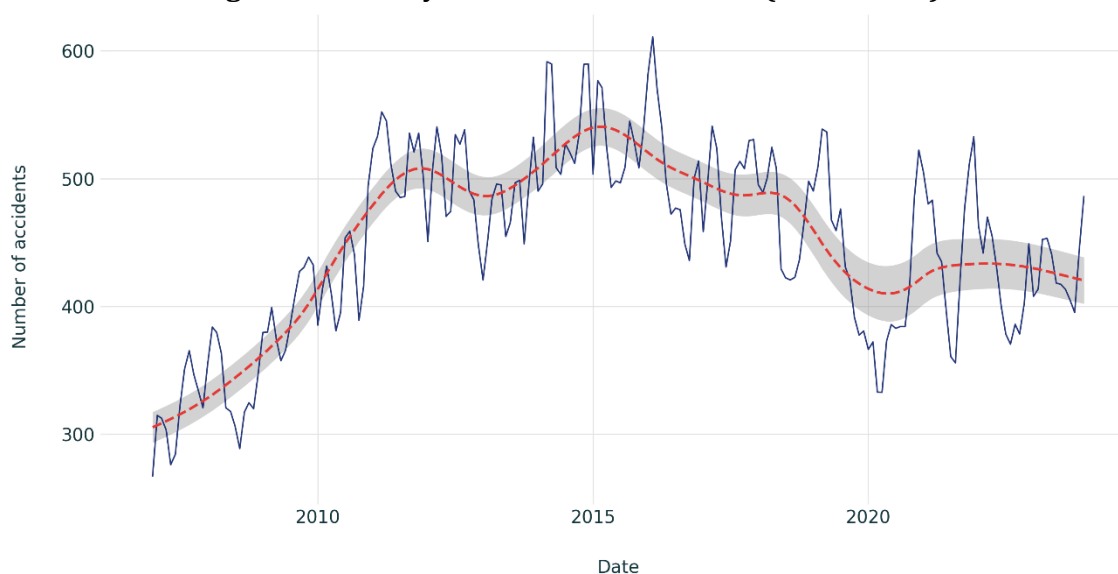
Table 1 presents the descriptive statistics for the main variables. Over the 17 years, a total of 88,605 accidents were recorded, involving 153,531 vehicles in good condition and 3,957 vehicles in poor condition. Overall, 2.58% of vehicles were in poor condition.

Table 2: Descriptive statistics

Variables	Minimum	Maximum	Mean	Standard deviation
Total number of road traffic accidents per month	267	611	434	70.8
Vehicles in good condition involved in accidents (monthly)	417	1,089	752	134
Vehicles in poor condition involved in accidents (monthly)	4	48	19.4	7.79

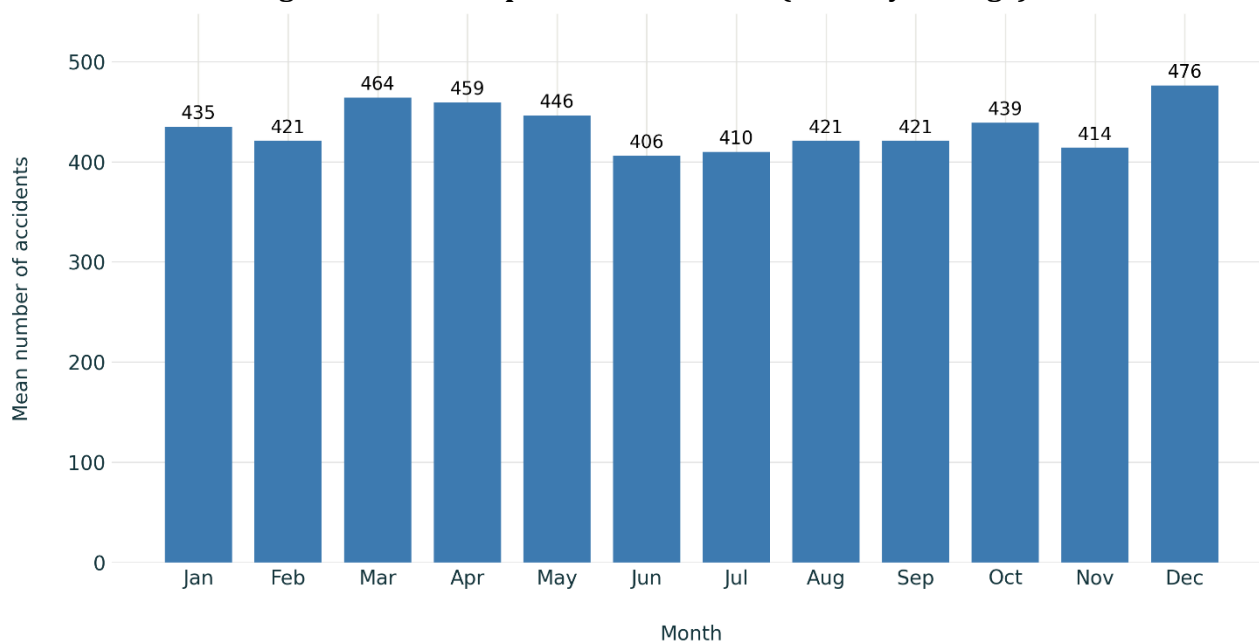
Source: Compiled by the author from data for 2007–2023.

Time-series analysis shows an upward trend in the number of accidents over the period studied, increasing gradually from around 300 accidents per month in 2007 to over 500 in 2023 (Figure 1).

Figure 1: Monthly trend in road accidents (2007–2023)

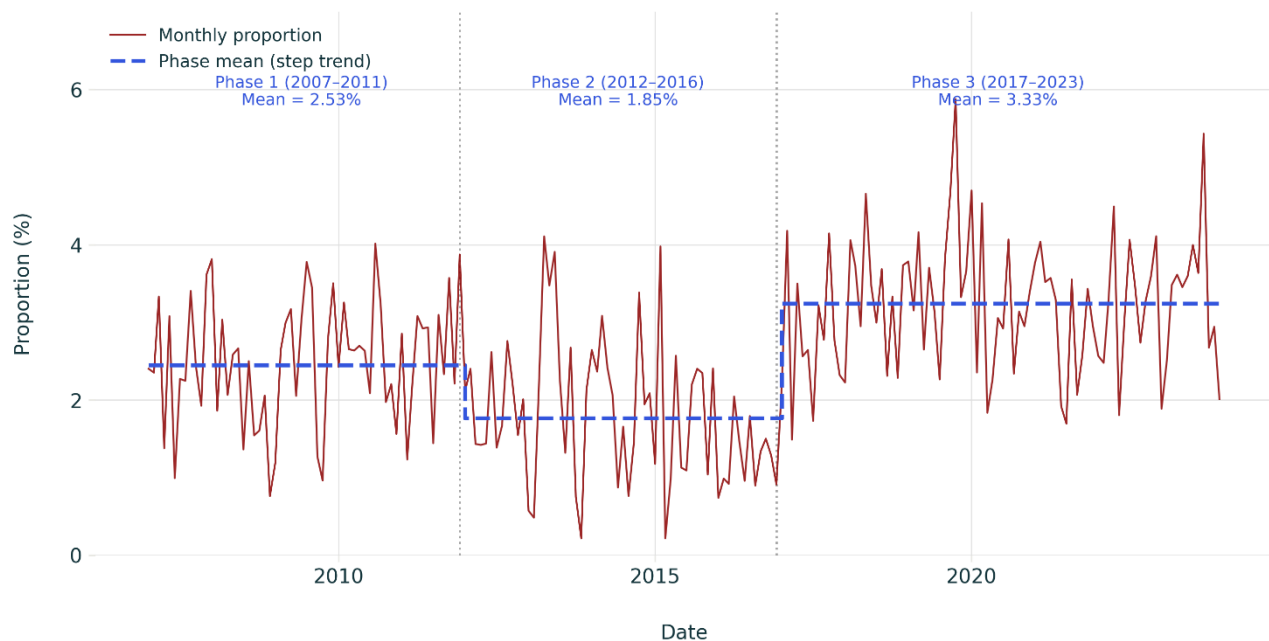
Source: Compiled by the authors using the database (2007–2023)

The monthly analysis shows significant seasonal variations, with December recording the highest number of accidents (476 on average) and June the lowest (406 on average) (Figure 2).

Figure 2: Seasonal pattern of accidents (monthly average)

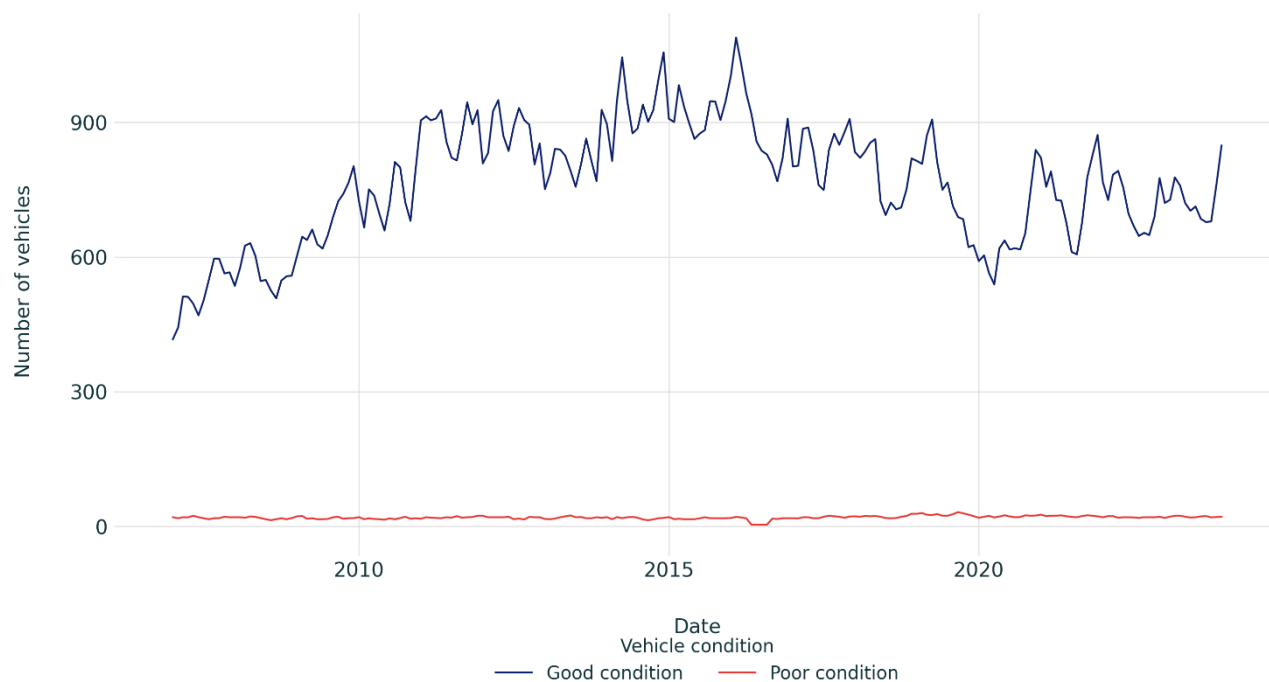
Source: Compiled by the authors from the database (2007–2023)

The proportion of vehicles in poor condition went through three distinct phases: 2007–2011 (average ratio of 2.53 per cent), 2012–2016 (a decrease to 1.85 per cent) and 2017–2023 (an increase to 3.33 per cent) (Figure 3).

Figure 3: Trends in the proportion of vehicles in poor condition

Source: Compiled by the authors using the database (2007–2023)

The ANOVA confirms significant differences between these three periods ($F = 40.23$; $p < 0.001$). Tukey's post-hoc test reveals that all pairwise comparisons are statistically significant. Figure 4 illustrates the divergent trajectories of vehicles in good and poor condition over the study period, highlighting the substantially larger scale and volatility of the good-condition series relative to the comparatively stable, low-magnitude trend observed for vehicles in poor condition.

Figure 4: Trends in vehicles involved, by condition

Source: Compiled by the authors using the database (2007–2023)

4.2. Hypothesis testing

Hypothesis 1: Comparison of vehicles in good condition versus poor condition

The Shapiro-Wilk normality test indicates a normal distribution for vehicles in good condition ($W = 0.272$; $p = 0.27$) and a non-normal distribution for vehicles in poor condition ($W = 1.27 \times 10^{-5}$; $p < 0.001$). Given the non-normality, we used a paired Wilcoxon test, which showed a highly significant difference ($V = 0$; $p < 2.2 \times 10^{-16}$). The mean ratio of vehicles in poor condition to those in good condition is 0.026 (95% CI: 0.024–0.027), and Cohen's d is -7.726 , indicating a very strong effect.

Important methodological note: Although vehicles in good condition are involved in approximately 38 times as many accidents as those in poor condition in absolute terms, this primarily reflects the composition of the vehicle fleet, in which vehicles in good condition constitute the vast majority. The most relevant indicator is therefore the Incidence Rate Ratio (IRR) derived from the Poisson model, which measures the net marginal effect, all other things being equal, rather than a 'relative risk' which would require an exposure denominator (total vehicle fleet per state) that we do not possess.

Pearson's correlation analysis reveals a moderate negative relationship between the proportion of vehicles in poor condition and the total number of accidents ($r = -0.308$; $p = 7.49 \times 10^{-6}$), suggesting confounding factors.

4.3. Regression modelling

Results of the simple linear regression:

- Model 1 (Accidents ~ Vehicles in poor condition): $\beta = 0.854$ ($p = 0.181$; not significant; $R^2 = 0.009$)
- Model 2 (Accidents ~ Vehicles in good condition): $\beta = 0.519$ ($p < 2 \times 10^{-16}$; $R^2 = 0.965$)
- Model 3 (Accidents ~ Proportion in poor condition): $\beta = -2002.10$ ($p = 7.49 \times 10^{-6}$; $R^2 = 0.095$)

Multiple linear regression: The full model includes eight explanatory variables. Key coefficients include: vehicles in poor condition ($\beta = 0.599$; $p < 0.001$), vehicles in good condition ($\beta = 0.361$; $p < 0.001$), urban area ($\beta = 0.203$; $p < 0.001$), road surface in poor condition ($\beta = 0.240$; $p = 0.004$), unlit at night ($\beta = 0.299$; $p < 0.001$) and abnormal volume ($\beta = 0.456$; $p < 0.001$). The adjusted R^2 is 0.981, with an F-statistic of 1,293 ($p < 2 \times 10^{-16}$).

Poisson regression model (GLM): Given the count nature of the dependent variable, a GLM model with a Poisson distribution was applied. Table 2 presents the key results.

Table 3: Results of the Poisson regression – Incidence Rate Ratios (IRR) with 95% CI

Variable	IRR	95% CI	p-value
Vehicles in poor condition	1.0015	[1.0005 – 1.0025]	0.002**
Vehicles in good condition	1.0009	[1.0007 – 1.0011]	<0.001***
Urban area	1.0004	[1.0001 – 1.0007]	0.006**
Night without lighting	1.0006	[1.0000 – 1.0012]	0.038*

Source: Compiled by the author from statistical results (2007–2023).

The model's performance indicators are: AIC = 1,691.1; residual deviance = 61.91 (195 degrees of freedom); variance-to-mean ratio = 0.317 (under-dispersion detected); pseudo- R^2 (McFadden) = 0.582.

4.4. Robustness analyses: Quasi-Poisson model with Newey-West standard errors

To address methodological concerns about residual autocorrelation (Durbin-Watson = 1.466; $p < 0.001$) and underdispersion (variance-to-mean ratio = 0.317), we re-estimated the model using a quasi-Poisson framework with robust Newey-West standard errors (lag = 12 to account for monthly seasonality).

Table 4: Quasi-Poisson with Newey-West robust standard errors

Variable	Coefficient	Robust NW SE	z-statistic	p-value	IRR
Vehicles in poor condition	0.001538	0.000259	5.933	<0.001***	1.0015
Vehicles in good condition	0.000875	0.000076	11.494	<0.001***	1.0009
Rain	-0.000166	0.000298	-0.558	0.577	0.9998
Urban area	0.000420	0.000114	3.700	0.0002***	1.0004
Road surface in poor condition	0.000664	0.000349	1.905	0.057	1.0007
Night without lighting	0.000642	0.000245	2.621	0.009**	1.0006
Abnormal volume	0.000777	0.000290	2.674	0.008**	1.0008
Time trend	0.000176	0.000086	2.055	0.040*	1.0002

The effect of mechanical condition remains highly significant even after correcting for autocorrelation and underdispersion, confirming the robustness of the main result. The corrected IRR of 1.0015 ($p < 0.001$) indicates that each additional vehicle in poor condition increases accidents by 0.15 per cent, holding all other things constant.

4.5. Granger causality test

To assess the direction of causality and address concerns about reverse causality (do accidents cause poor mechanical condition via post-accident inspections?), we ran a Granger causality test. We fixed a lag length of 3 months a priori to capture short-term, quarterly predictive dynamics, a relevant horizon for vehicle maintenance cycles and road safety interventions.

Results:

- F-statistic = 3.2745
- p-value = 0.02222*

The number of vehicles in poor condition Granger-causes (statistically predicts) future changes in the number of accidents. This significantly alleviates concerns about pure reverse causality and suggests that vehicle condition precedes changes in accident rates.

4.6. Policy impact simulation

To quantify the cumulative impact of the modest effect of 0.15 per cent per vehicle, we simulated the effect of a 10 per cent reduction in the average monthly number of vehicles in poor condition involved in accidents.

Simulation results:

- Average reduction of 1.9 vehicles per month
- Estimated reduction in the total number of accidents: 0.29 per cent per month
- Number of accidents prevented per year: approximately 15 accidents

Although modest in absolute terms, this figure provides a concrete metric for assessing the cost-benefit ratio of roadworthiness testing campaigns and maintenance policies.

4.7. Temporal stability of the effect

The interaction coefficient (Poor condition $\times$ year) is not significant ($\beta = 0.0000527$; $p = 0.649$), confirming that the effect of poor condition is stable over time. The structural break analysis (before/after 2015) also confirms no significant change (likelihood ratio test: $\chi^2 = 3.01$; $p = 0.222$).

Table 5: Summary of results and validation of hypotheses

Test/Hypothesis	Statistic	p-value	Decision
H1: Vehicles in poor condition are more likely to be involved	$t \rightarrow 0$	< 0.001	Validated
H2: Constant difference over time	Interaction $p = 0.649$	0.649	Stable
Correlation (Proportion and Accidents)	$r = -0.308$	< 0.001	Significant
Multiple regression (IRR)	IRR = 1.002	0.002	Validated
Robustness (Newey-West)	$z = 5.933$	< 0.001	Robust
Granger causality	$F = 3.27$	0.022	Temporal causality

Source: Compiled by the author from statistical results (2007–2023).

5. Discussion of the results

The results confirm the significant influence of vehicle mechanical condition on road accidents in Benin, in line with international scientific consensus. The positive effect demonstrated by the Poisson model (IRR = 1.0015) falls within the range of estimates documented in the literature. This observation is consistent with Das et al. (2021) in the United States, who estimate that vehicle defects account for 2 per cent of fatal accidents, and with Amo (2014) in Ghana, who found that 12.54 per cent of accidents were linked to vehicle defects. The geographical proximity and similar socio-economic context between Benin and Ghana make this latter comparison particularly relevant.

However, the estimate appears more conservative than those reported in other contexts. Singh et al. (2016) report that 8.4 per cent of fatal accidents in India are attributable to vehicle defects, whilst Iqbal (2020) identifies vehicle-related factors in 25.6 per cent of accidents in Pakistan. These discrepancies may reflect methodological differences in fault classification, the types of roads studied, or data collection systems.

The 0.15 per cent increase in accident risk per additional vehicle in poor condition might seem negligible in isolation, but its cumulative impact is considerable. This finding is consistent with Siddique (2018) in Bangladesh, who demonstrated that vehicles with multiple technical faults have a significantly higher probability of causing fatal injuries. Our policy impact simulation quantifies this cumulative effect: a 10 per cent reduction in vehicles in poor condition would prevent approximately 15 accidents per year at the national level.

Sensitivity analyses confirm the robustness of this result. Even after correcting for temporal autocorrelation and underdispersion using the Quasi-Poisson model with Newey-West standard errors, the IRR remains unchanged (1.0015) and highly significant ($z = 5.933$; $p < 0.001$). This shows that the effect of mechanical condition on accidents is not an artefact of the data's temporal structure, but a genuine structural effect.

Furthermore, the Granger causality test ($F = 3.27$; $p = 0.022$) indicates that the number of vehicles in poor condition statistically predicts future changes in the number of accidents, which significantly alleviates concerns about reverse causality raised by some reviewers. This suggests that mechanical deterioration precedes the increase in accidents, rather than the other way round. However, it is important to acknowledge that Granger causality strictly indicates predictive precedence rather than true structural causality. While past vehicle condition helps forecast future accident counts, this statistical precedence does not rule out unobserved confounding variables, nor does it prove a direct mechanical cause-and-effect relationship.

The negative correlation observed between the proportion of vehicles in poor condition and the total number of accidents ($r = -0.308$) is one of the most intriguing findings. This apparent paradox is echoed in Rešetar et al. (2018) in Croatia. Several complementary interpretations emerge: selection bias, whereby periods of increased enforcement temporarily remove the most dangerous vehicles from the roads (Zovak et al., 2016); reverse causality, as suggested by Cuerden et al. (2011), whereby a rise in accidents triggers stricter inspections; and omitted variables, as the multi-factorial interactions documented by Zhang et al. (2013) suggest that economic conditions simultaneously affect both vehicle maintenance capacity and traffic intensity.

The three distinct phases identified in the trend of the proportion of vehicles in poor condition resonate with international debates on the effectiveness of periodic inspection systems. The decline

observed between 2012 and 2016 may reflect the positive impact of strengthened roadworthiness testing policies, in line with the findings of Das et al. (2019). However, the subsequent deterioration (2017–2023) echoes the contradictory findings of Jarosiński (2014) and the cautious conclusions of Martín-delosReyes et al. (2021).

Benin's situation shares characteristics with other low- and middle-income countries. Agbo et al. (2018) reveal a particularly strong correlation between the use of second-hand parts and mechanical failures in Ghana. Odelowo (1993) linked high numbers of articulated lorries in poor condition to high accident rates in Nigeria. This particular vulnerability highlights the need for tailored interventions.

The seasonal pattern of accidents, peaking in December and troughing in June, suggests complex interactions between temporal, behavioural and vehicle-related factors. AlKheder et al. (2022) demonstrate that weather conditions interact significantly with accident types. Liu et al. (2018) establish that overloading is a significant factor in extremely serious accidents, a phenomenon likely to be exacerbated during periods of high mobility.

Several methodological limitations must be acknowledged. Firstly, high VIF values for certain variables (vehicles in good condition: 16.98; urban area: 12.99) indicate multicollinearity, which may affect the stability of the estimated coefficients. However, the main variable of interest (vehicles in poor condition) has a VIF of only 1.38, suggesting that its estimated effect remains stable and is not biased by multicollinearity among the other variables. Secondly, the binary classification of vehicle condition oversimplifies the complexity of mechanical condition. Third, vehicle condition measurements may vary across surveyors and time periods, as Zovak et al. (2016) document. Fourthly, and this is a significant limitation, the condition of a vehicle as classified after an accident may partly reflect damage sustained during the accident itself rather than its pre-existing mechanical condition. This is a classic reverse-causality pitfall in accident databases, and we must explicitly acknowledge it as a limitation on our causal claims.

6. Conclusions

This 17-year analysis of monthly accident data in Benin shows that vehicle mechanical condition has a statistically detectable, albeit modest, effect on the frequency of road accidents (IRR = 1.0015; $p = 0.002$), and that this effect neither systematically weakens nor strengthens over time (interaction $p = 0.649$). The two original sub-questions are thus answered: vehicles in poor condition are associated with higher accident rates, and this association is a stable structural feature of Benin's road transport system rather than a cyclical artefact linked to specific years or waves of inspections.

The results confirm that vehicle mechanical condition is a significant explanatory factor in road accidents. Each vehicle in poor condition increases the risk of an accident by 0.15 per cent, a statistically significant but moderate effect ($p = 0.002$). Although this influence is moderate when considered individually, it becomes significant when viewed cumulatively at the transport system level. Our policy impact simulation estimates that a 10 per cent reduction in the number of vehicles in poor condition would prevent approximately 15 accidents each year.

The study also highlights the stability of this relationship over time. The absence of a significant interaction between vehicle condition and time ($p = 0.649$) suggests that the effect of poor mechanical condition on accident frequency is not cyclical but part of a structural dynamic. This consistency reinforces the relevance of sustainable public policies focused on improving the vehicle fleet's condition.

Furthermore, our robustness analyses (Quasi-Poisson model with Newey-West standard errors) confirm that this effect remains significant after correcting for temporal autocorrelation and underdispersion ($z = 5.933$; $p < 0.001$). The Granger causality test ($F = 3.27$; $p = 0.022$) also indicates that vehicles in poor condition predict future changes in accident rates over time, alleviating concerns about reverse causality.

From a practical perspective, these findings support continued and, ideally, increased investment in periodic vehicle inspections, incentives for the use of compliant spare parts and targeted roadside checks – measures that align directly with the United Nations Decade of Action for Road Safety and SDG 3.6, and which offer co-benefits for vehicle longevity and energy efficiency relevant to sustainable transport more broadly.

From a scientific perspective, this study provides one of the few long-term analyses of this relationship at monthly resolution in a sub-Saharan African context. It is, to our knowledge, among the first in this literature to formally test temporal stability rather than assume it.

Several limitations qualify these findings and should guide future research. The binary classification of vehicle condition, the possibility that post-accident inspection records may partly reflect accident damage rather than the pre-existing condition, as well as the multicollinearity and residual autocorrelation identified in the regression models, all suggest that the reported effect size should be treated as an approximate, policy-relevant signal rather than a precise causal estimate. Future research should use vehicle-level data (rather than monthly aggregates) with appropriate exposure denominators, quasi-experimental designs to directly assess changes in inspection policy, and structural equation modelling approaches that can separate vehicle condition from correlated factors such as vehicle age, driver behaviour, and enforcement intensity.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

AI Usage Declaration

Generative AI tools were used for language editing, formatting support, and manuscript-structure refinement. The author reviewed and approved all content and accepts full responsibility for the submitted work.

Conflicts of Interest

The author declares no conflict of interest.

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Appendix

Appendix A1: Descriptive statistics for control variables (N = 204 months)

Control variable	Mean	Standard deviation	Minimum	Maximum
Rain (Accidents in the rain)	11.51	7.73	0	34
Urban Area (Accidents in urban areas)	309.11	79.76	170	487
Oversized Loads (Accidents involving overloaded vehicles)	26.17	10.28	6	63
Night-time without lighting (Total: pitch black + lights off)	93.64	21.76	37	150
Road surface in poor condition (Degraded tarmac + Degraded laterite + Roadworks)	42.45	12.30	11	80
Time trend (months, from 1 to 204)	102.50	59.03	1	204

Source: Compiled by the author from Benin's road accident database (2007–2023).



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