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A Bayesian analysis of the impact of post-crash care on road mortality in Sub-Saharan African countries

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ABSTRACT

Sub-Saharan Africa is undergoing a disproportionate road tragedy compared to its motorization rate and road network density. Most of the road traffic deaths occur in the pre-hospital phase. Yet, more than half of the African countries do not possess formal pre-hospital care system. This study assesses the potential impact of post-crash care on road mortality in 23 Sub-Saharan African countries. A panel Bayesian normal linear regression with normally distributed non-informative priors is used to fit the data set covering the time period 2001–2010. The post-crash care system is proxied by the estimated share of seriously injured transported by ambulance, and three binary variables indicating the existence of emergency access telephone services and emergency training for doctors and nurses. The findings suggest a negative correlation between the road mortality rate and the estimated share of seriously injured transported by ambulance, the emergency access telephone services and the emergency training for doctors. A positive relation is unexpectedly observed for the emergency training for nurses. Other regressors such as the Gross Domestic Product per capita and populations in the age range 15–64 years are related to higher fatality rates while the length of the road network and life expectancy are linked to decreasing fatality rates.

1. Introduction

Road accidents are a concerning issue in Africa. The continent faces a disproportionate road tragedy compared to its motorization rate and road network density [1–3]. Every day, tens of thousands of injuries and deaths occur on African roads putting a huge financial and economic burden on populations. More than 75% of the victims are in the productive age range of 16–65 years and the vulnerable road users account for over 65% of the deaths [4]. Unless suitable actions are undertaken, road traffic injuries are predicted to be ranked as the fifth cause of mortality in Africa by the year 2030 [1].

Post-crash care must be a critical component of the actions to undertake because most of the road traffic deaths in Africa occur in the pre-hospital phase [5]. However, more than half of the African countries do not possess formal pre-hospital care system [1] and they transport less than 10% of the injured in ambulances [6]. Although the primary objective is to prevent the occurrence of road traffic accidents, more can be done to curb crash-related injuries. The availability of a suitable post-crash emergency care system is a key to achieving this decrease [2,7–10]. Post-crash emergency care encompasses emergency rescue, pre-hospital medical care and victims' immediate transportation following road crashes [11,12]. Bishai et al. [13] associated the decline in traffic deaths in the developed countries to the post-injury ambulance transport and medical care. The probability of dying in motor-vehicle accidents was 10% lower in American States having organized trauma systems compared to their counterparts which did not possess such systems [14]. Van Beeck et al. [15] cited the amelioration of trauma care among the explaining factors of the decline in road mortality in some 21 industrialized countries from 1962 to 1990. Bjornstig [16] estimated a decrease of almost 20% in the Swedish traffic fatality rate among accidents victims who were not instantly killed. The author attributed this decline to the ameliorations in post-crash care.

Yet, many of the African countries are inadequately prepared in terms of emergency medicine to succor road accidents survivors [6]. Limitations appear at all the levels of the rescue chain [1,6]. Most often, crash victims wait for hours before receiving appropriate assistance because of the shortage in the number of ambulances and qualified staff, the poor communication between trauma centers and the police as well as the congestion that delays emergency cars. As a result, needless deaths occur [3].

In spite of this critical situation, road fatalities have not been appropriately considered in the design of health and development agendas in

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low and middle-income countries [2]. Consequently, rigorous empirical investigations about the effects of post-crash emergency services on road crash mortality are necessary to persuade decision-makers about the benefits of these services. To the authors' knowledge these kinds of investigations are missing in Sub-Saharan Africa (SSA). Therefore, this study is designed to examine the impact of post-crash care policies on road accidents mortality rate in this part of the African continent.

In what follows, Section 2 summarizes previous studies related to road post-crash measures and their effectiveness. The data and the estimation technique are respectively described in Sections 3 and 4. The results are presented and discussed in Section 5 while Section 6 provides the conclusions and recommendations.

2. Literature review

The prompt response of the emergency staff to crashes occurrence is an essential element to saving lives [10,17]. Accordingly, most of the studies dealing with emergency and trauma care focused either on crash notification time or on the emergency medical services (EMS) response time.

Li et al. [18] suggested the implementation of an automatic crash notification (ACN) system in Taiwan given the high rate of pre-hospital deaths especially in rural areas where victims are transported over long distances to care centers. Using Finnish data over the period 2001–2003, Virtanen et al. [19] revealed the ability of the ACN system to annually preclude between 5 and 10% of the fatalities. Using simulations, Taute [20] reported a decrease of 32% and 42% in the EMS response time respectively in the city and outskirts of Pretoria, South Africa, if an ACN policy is implemented in the entire city. Based on a data set of 1997, Clark and Cushing [21] reported an annual decline from 1.5% to 6% in traffic mortality in the United States due to the implementation of an ACN system. Lahausse et al. [22] found that the Australian road mortality would annually decrease by 10.8% were all vehicles equipped with the ACN system.

Noland [23] assessed road crash fatalities in some OECD countries over the period 1970–1996. The evaluation revealed a reduction of fatalities in the range of 5 to 25% as a result of the progress in medical care and technology such as the EMS. Likewise, Gonzalez et al. [24] used a 2-year, data set for the entire State of Alabama in the United States. They found that a prompt reaction of the EMS after motor vehicles crash notifications was highly associated with mortality reduction, especially in rural areas which previously witnessed greater traffic fatalities. In a similar study from the State of Utah, Wilde [25] evaluated the EMS response time on mortality of all patients including road crash victims. The analysis concluded that an additional minute in the reaction time triggered an increase of the mortality in the range of 8 to 17%. Sánchez-Mangas et al. [26] used a probit model to study the link between the probability of dying from road traffic accidents and the EMS response time in Spain. The study considered 1400 accidents in May 2004. It showed that a decrease by 10 min in the response time induced a reduction of 33% and 32% respectively in motorway and conventional road accidents deaths. Arroyo et al. [27] conducted a similar study in Spain with a data set of May 2004. Using a Bayesian probit and logit, they found that a decrease by 5 min in the response time lowered the probability of dying by 24% and 30% respectively for roads and motorways accidents.

In a nutshell, previous studies reported that post-crash care is an effective tool to curb traffic-related death toll.

3. Data description

The road safety data in the African Region are still of poor quality [1,6,8,28]. As a result, 23 SSA countries, as shown in Table 1, are considered in the study because the remaining ones do not provide measurements for as many variables and years as these 23.

Table 1
List of the 23 countries included in the study.

Countries
Benin
Botswana
Cameroon
Cape Verde
Côte d'Ivoire
Democratic Republic of Congo
Ethiopia
The Gambia
Ghana
Kenya
Lesotho
Mauritania
Mozambique
Namibia
Niger
Nigeria
Rwanda
Sao Tome and Principe
Senegal
South Africa
Sudan
Swaziland
Tanzania

The sample includes Ethiopia, Nigeria, South Africa, and Sudan which together account for half of the road injury death toll in SSA [28]. The data set covers the time period 2001–2010. Table 2 provides detailed descriptions of the variables used in the analysis. The variables of interest, the emergency-related variables, as identified by the World Health Organization [2] are the estimated share of seriously injured carried by ambulance and three indicator variables (emergency phones, emergency doctors and emergency nurses). All these variables are expected to be linked to lower mortality rates.

Based on the data availability, other variables deemed to have an impact on traffic-related fatalities and injuries are included in the analysis. The Gross Domestic Product per capita (GDPPC), population-related variables and the life expectancy have been collected from the World Development Indicators database of the World Bank while the length of the road network is from the African development Indicators 2010 of the World Bank [29]. Nevertheless, the length of road network is invariant in each country over the study period because it is not consistently collected due to situations such as conflicts. It should consequently be considered as indicating trends [29]. The remaining variables are obtained from the Global status report on road safety of the World Health Organization [2]. The dependent variable is the road mortality rate (ROADM) which is defined in the study as the number of deaths per 100,000 population. Different definitions of the concept of mortality rate are used by countries ranging from “died on the scene” to “unlimited” [2]. Therefore, data about the fatalities are adjusted to 30 days in order to mitigate the effects of these differences and compensate for underreporting in some countries [2].

The data were scrutinized through an ordinary least squares regression to detect outliers. The detected outliers were found to have no impact on the estimation results. The correlation between the variables was also inspected through the correlation matrix shown in Table 3.

ROADM is highly correlated with GDPPC and POP64. The two latter variables also show high correlation. These high correlations are likely to cause multicollinearity which may misrepresent the statistical significance of the estimates. However, the analysis revealed no multicollinearity as attested in Table 4 by the highest value of the variance inflator factor (VIF) which is 3.96; a highest VIF less than 10 suggesting the absence of multicollinearity [30].

Three of the four variables of interest are binary variables which could have been continuous if data were available. When data are limited, it is appropriate to use a modeling technique that incorporates prior

Table 2
Descriptive statistics of the data set.

Variables	Description	Mean	SD	Min	Max
ROADM	Number of deaths per 100,000 population	9.549	7.693	0.436	33
GDPPC	Gross domestic product per capita (current US$)	1256.658	1456.818	112.237	7175.625
POP64	Percentage of population of age between 15 and 64	54.386	3.623	43.694	65.063
ROADNET	Length of total road network (kilometers)	55,906.7	81,138.42	320	364,131
EXPECT	Life expectancy at birth, total (years)	54.889	6.628	43.533	73.857
EPHONE	Index variable that takes the value 1 if there is an emergency access telephone number(s) service	0.696	0.461	0	1
EAMB	Estimated percentage of seriously injured transported by ambulance	27.784	28.290	0	75
EDOC	Index variable that takes the value 1 if there is an emergency medicine training for doctors	0.696	0.461	0	1
ENUR	Index variable that takes the value 1 if there is an emergency medicine training for nurses	0.391	0.489	0	1

information about them [31,32]. Even when the data are available, they are likely to be plagued with errors and provide estimates which are not informative [33]. Therefore, this study uses the Bayesian method because it allows the combination of a prior distribution of the parameters with the current distribution of the data to provide a posterior distribution.

The Bayesian method offers a quite different alternative to explore statistical inference and modeling. It has the capacity to cope with problems such as over-dispersion and uncertainty related to the data, and provides viable results even for small sample sizes [34–36]. The safety of any entity is generally assessed using past information about its accident counts. The Bayesian technique fits this kind of assessment by using accidents history of similar entities [34]. This technique has been progressively improved in road safety modeling to become a viable approach to quantify the expected outcome about traffic fatalities [37].

4. Method

The dependent variable, the road mortality rate, having a continuous distribution, can be estimated using a linear model. Thus, panel and non-panel Bayesian normal linear regressions are estimated in this study.

4.1. Bayesian inference

In the Bayesian method, the parameters are considered as random variables having their own distribution unlike the classical methods in which parameters are considered as constants. For a given model, the Bayesian method consists in computing the posterior distribution of its parameters by combining two statistics: the prior distributions of the parameters and the likelihood distribution of the data. Say $P(\beta,\sigma^2/y)$, the posterior distribution of the parameters β and σ^2 given the observed data set y; $P(\beta,\sigma^2/y)$ is proportional to the likelihood distribution of the data and the prior distributions of the parameters. The relation is written as

$$\text{Posterior} \propto \text{Likelihood} \times \text{Prior}$$

or

$$P(\beta,\sigma^2/y) \propto L(y/\beta,\sigma^2) \times \pi(\beta,\sigma^2)$$

where $P(\beta,\sigma^2/y)$, the posterior distribution summarizes the information the researcher has after visualizing the data; $L(y/\beta,\sigma^2)$ is the likelihood function of the data given the parameters; it refers to the distribution of the observed data, and $\pi(\beta,\sigma^2)$ represents the prior distributions of the parameters.

The gist of the Bayesian approach is that all the extra information besides the data concerning the parameters can be integrated into the model through the prior distributions [32]. These distributions embody the set of non-data information available regarding the model parameters. In other words, $\pi(\beta,\sigma^2)$ reflects any information the researcher possesses about the distribution of the parameters before observing the data set [38,39].

The prior can be informative (presence of prior information) or non-informative (lack of prior information) [40,41]. An informative prior provides trustworthy information from previous studies or expert knowledge on the parameter of interest [32]. In that case, it is appropriate to incorporate such evidence into the prior distributions. However, if no credible previous knowledge is available, the prior is considered as non-informative (also known as flat, diffuse or vague prior) [32,42,43]. This type of prior equally weighs the posterior distributions of all parameters [32,44].

4.2. Convergence diagnostic

After setting the prior distributions, initial values are attributed to the parameters. The model is then calibrated using the Markov Chain Monte Carlo (MCMC) algorithm implemented in software such as Stata and OpenBUGS. Nevertheless, before reporting the estimation results, the convergence of all the parameters in the model should be assessed to ensure that the MCMC chain adequately covers the posteriors. There are several techniques to check the convergence. (see [39] for a detailed discussion). Among them is the visual inspection of the MCMC trace plots to verify their stationarity. A common technique is

Table 3
Correlation matrix.

	Roadm	Gdppc	Pop64	Roadnet	Expect	Ephone	Eamb	Edoc	Enur	Year
Roadm	1									
Gdppc	0.769	1								
Pop64	0.810	0.833	1							
Roadnet	0.236	0.357	0.431	1						
Expect	−0.102	−0.035	0.009	−0.280	1					
Ephone	0.055	0.208	0.141	0.207	−0.108	1				
Eamb	0.214	0.361	0.330	0.307	−0.122	0.517	1			
Edoc	0.082	0.202	0.086	0.174	−0.197	0.589	0.484	1		
Enur	0.209	0.170	0.233	0.340	0.002	0.337	0.316	0.530	1	
Year	−0.023	0.247	0.133	0.000	0.197	0.000	0.000	0.000	0.000	1

Table 4
Variance Inflator Factor (VIF) scores.

Variable	VIF	1/VIF
POP64	3.96	0.252
GDPPC	3.90	0.257
EDOC	2.25	0.444
EPHONE	1.73	0.580
ENUR	1.68	0.596
EAMB	1.65	0.604
ROADNET	1.53	0.655
EXPECT	1.24	0.804
YEAR	1.15	
Mean VIF	2.12	

to compute the Brooks Gelman-Rubin (BGR) convergence statistic for each parameter; a statistic under 1.2 implying convergence [45,46].

4.3. Model comparison

If many Bayesian models are estimated, there is a need to select the one that best fits the data. The deviance information criterion (DIC) by [47] is the statistic frequently used to assess the goodness-of-fit of Bayesian models. The DIC is specified as: $DIC=\overline{D}+p_D$ where $\overline{D}$ refers to the posterior mean of the deviance while p_D is the actual number of parameters and indicates the complexity of the model. Models with lower DICs are favored. A difference of more than 10 between two DICs eliminates the model with the highest DIC [47].

4.4. Random effects panel model

The most popular approaches to model panel data are the fixed effects (FE) and the random effects (RE). Three of the four variables of interest being time-invariant; an RE model is adopted because the FE model has the drawback of ignoring these kinds of variables in non-Bayesian models [48]. Also, the FE model supposes an individual-specific constant term. Yet, it makes more sense to assume a similarity between the different constants. This can be performed using the Bayesian RE model [49].

Eq. (1) represents the RE panel structure of a regression model having a dependent variable y_{it} referring to the road mortality rate of country i at time t, a normally distributed disturbance term ε_{it} and k regressors $x_{1it},\ldots,x_{kit}$ for $i=1,\ldots,N$ and $t=1,\ldots,T$.

$$y_{it}=\alpha+\beta_1x_{1it}+\ldots+\beta_kx_{kit}+u_i+\varepsilon_{it} \tag{1}$$

where $\varepsilon_i\sim N(0,\sigma^2)$; $y_i\sim N(\mu_i,\sigma^2)$, α is the constant term; β_k $(k=1,\ldots,K)$ are the regression coefficients and u_i represents the RE term.

The Bayesian analysis is concerned with the estimation of the average mortality rate μ_i with $\mu_i\sim N(0,\tau)$ where $\tau={}^1/_{\sigma^2}$ represents the precision parameter of the model [50,51]. The panel Bayesian model is then formulated in Eq. (2) as

$$\mu_{it}=\alpha+\beta_1x_{1it}+\ldots+\beta_kx_{kit}+u_i+\varepsilon_{it} \tag{2}$$

where prior distributions are assigned to all the parameters in addition to the RE term.

In the absence of credible knowledge regarding these distributions in the literature review about the topic, non-informative priors are considered as commonly assumed in transportation [52] and used in studies such as [32,53,54]. The most frequently used non-informative priors are those that are normally distributed with a mean of zero and a large variance [55]. Following [47], the normally distributed non-informative priors $N(0,10^{-5})$ are used in this study with a precision parameter τ being gamma distributed as $dgamma(10^{-3},10^{-3})$.

5. Results and discussion

Overall, four models are estimated. In Model 1, an ordinary least squares (OLS) regression is estimated with clusters at the country level to control for the possible heteroskedasticity of the disturbance terms and the autocorrelation between them. The Bayesian counterpart of this model is a Bayesian multivariate normal linear regression (Model 2). The equivalents of Models 1 and 2 are also estimated in a panel structure respectively in Models 3 and 4. Model 3 is a linear RE panel regression in order to control for time-invariant post-crash care-related variables while Model 4 is a panel Bayesian multivariate normal linear regression with RE. Comparing the non-Bayesian to the Bayesian methods is appropriate to assess how effective is the integration of uncertainty in the models. Models 1 to 3 were fitted using the Stata software [56] while Model 4 was coded in the OpenBUGS 3.2.3 software [57] because it allows the specification of the RE in Bayesian models. The estimation results are presented in Table 5 and Table 6.

In spite of having a lower AIC than Model 1 (OLS), Model 3 (RE-linear panel) is believed to be outperformed by the remaining models because its estimates have several limitations. Firstly, this model is not globally statistically significant at the 5% significance level because the p-value of its likelihood ratio statistic is greater than 5%. Secondly, the coefficients estimates of the variables GDPPC and ROADNET have opposite signs compared to the remaining models. While the sign (positive) for ROADNET can be justified because more roads may increase traffic exposure along with the risk for more fatalities, the (negative) sign for GDPPC is quite unlikely for a sample of non-developed countries [58] as explained later in the paper. Lastly, Fig. 1 shows a better agreement between the observed and the predicted values of the dependent variable for Models 1 and 2 compared to Model 3 where this agreement is very poor.

Models 1 and 2 present similar graphical patterns because most of the posterior mean estimates in Model 2 are similar to their counterparts in the OLS estimates in Model 1 as expected in the presence of non-informative priors [56].

As can be seen in Table 5 none of the variables of interest is statistically significant in Model 1. However, in Model 2, all the coefficients

Table 5
Non-panel estimation results for the number of deaths per 100,000 population.

Regressors	Model 1 - OLS	Model 2-Non-panel Bayesian		
	Parameter	Mean	SD	95% BCI
GDPPC	0.002** (2.62)	0.002	0.0002	(0.001, 0.003)
POP64	1.200** (3.12)	1.232	0.030	(1.167, 1.287)
ROADNET	−2e−05* (−1.73)	−1.9e−05	3.40e−06	(−2.65e−05, −1.34e−05)
EXPECT	−0.162 (−1.60)	−0.165	0.012	(−0.187, −0.141)
EPHONE	−1.261 (−1.21)	−0.019	0.008	(−0.036, −0.002)
EAMB	−0.018 (−0.64)	−1.264	0.009	(−1.280, −1.240)
EDOC	−0.738 (−0.50)	−0.734	0.004	(−0.742, −0.725)
ENUR	2.266 (1.37)	2.232	0.042	(2.149, 2.279)
YEAR	−0.477** (−3.49)	−0.478	0.0006	(−0.479, −0.477)
CONSTANT	909.932** (3.31)	909.906	0.025	(909.860, 909.956)
σ^2		14.157	0.018	(14.146, 14.169)
R-squared	0.770			
AIC	1272.168			
DIC		1262.265		
Countries	23	23		
Observations	230	230		

Note: two-tail significance tests. The t-statistics for the coefficients are given in parenthesis for Model 1.
** 0.05 level.
* 0.10 level.

Table 6
Panel RE estimation results for the number of deaths per 100,000 population.

Regressors	Model 3 – Linear Panel	Model 4 - Panel Bayesian		
	Parameter	Mean	SD	95% BCI
GDPPC	−0.0006** (−2.28)	0.0003	0.0001	(0.0002, 0.0004)
POP64	0.065* (0.54)	0.792	0.025	(0.497, 1.090)
ROADNET	1.46e−05 (0.67)	−3.8e−06	1.68e−06	(−1.9e−05, −2.66e−05)
EXPECT	−0.074 (−0.83)	−0.170	0.009	(−0.301,−0.038)
EPHONE	−1.477 (−0.33)	−1.304	0.005	(−1.946, −0.662)
EAMB	0.061 (0.88)	−0.023	0.001	(−0.031, −0.015)
EDOC	−1.396 (−0.28)	−1.025	0.002	(−1.095, −0.955)
ENUR	2.739 (0.68)	2.507	0.037	(2.305, 2.695)
YEAR	0.044 (0.61)	−0.026	0.0003	(−0.028, −0.023)
CONSTANT	−78.489 (−0.56)	27.590	0.014	(19.780, 35.430)
σ^2		5.892	0.011	(4.888, 7.103)
Log likelihood	−498.545			
Likelihood ratio statistic	10.38 (0.320)			
AIC	1021.09			
DIC		1030		
Countries	23	23		
Observations	230	230		

Note: two-tail significance tests. The t-statistics for the coefficients and the p-value for the likelihood ratio are given in parenthesis for Model 3.
* 0.10 level.
** 0.05 level.

appear as significant predictors of the road mortality rate because none of the Bayesian credit intervals (BCI) contain the value of 0 [59]. This suggests that the incorporation of the uncertainty has improved the estimations. Model 2 accordingly fits the data better than Model 1. This is in line with [53] who advocated that non-informative priors provide better estimates than frequentist methods in case of small sample sizes.

The estimates of Model 2 were obtained after 25,000 iterations with the first 5000 discarded as burn-ins and 20,000 kept. Model 4, instead, resulted from 50,000 iterations, the initial 15,000 of which were excluded as burn-ins and 35,000 retained as sample size. The two models were run from a 2-chain MCMC simulations and the convergence of each of them was assessed based on the visual inspection of the MCMC chains and the Brooks Gelman-Rubin (BGR) statistics which must be inferior to 1.2 for each parameter [45,46]. Model 4 fits the data better than Model 2 as it has the lowest DIC. Model 4 even rules out the latter because the gap between the two DICs is more than 10 [47]. Thus, the data appear to be best fitted using the panel Bayesian scheme whose results are analyzed in what follows.

In Model 4, the coefficient of the GDPPC is significantly correlated with more fatalities. This result is not surprising because the study sample is composed of non-developed countries. Being in the early stages of their developments, these countries are financially less able to establish adequate institutions that can formulate and implement traffic safety policies to curb the number of accidents and fatalities. Other more pressing issues draw resources and political attention away to the detriment of road safety [58]. In the same vein, Bezabeh [4] reported road safety in most African countries as still not being part of governments' priorities due to the many contending issues. The same report also found a positive correlation between road crash and the GDPPC.

The population of age between 15 and 64 is significantly related to higher fatality rates; this age range includes the most active populations. They are exposed as pedestrians, bicyclists, motorcyclists, passengers and alcohol impaired drivers.

The total length of road network and life expectancy are significantly connected to lower fatality rates. Life expectancy is likely to be perceived as a proxy for the improvements in medical care since greater access to quality health care services is a key element among the factors that affect its length [60–62].

As far as the four post-crash care variables are concerned, three of them (EPHONE, EAMB and EDOC) provide the expected results. The coefficient of the emergency telephone indicator (EPHONE) has the expected statistically significant negative sign. An emergency care system operates at best if there is an efficient communication network to support it. "The best teams equipped with state-of-the-art technology and supplies will be wasted if they cannot reach patients quickly or if they have no contact with the hospitals where their patients are to be

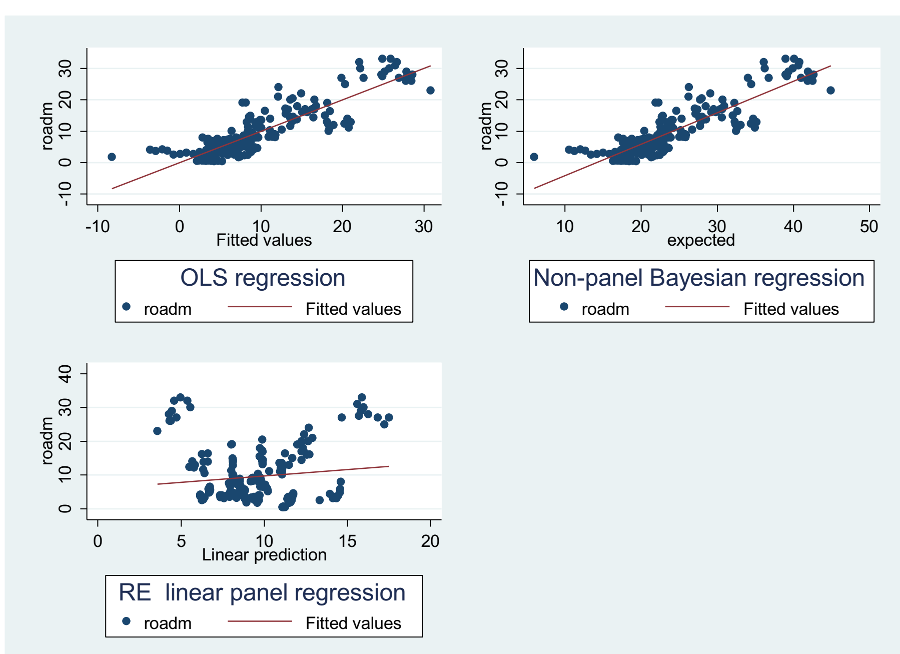

Fig. 1. Plots of the observed vs. predicted values of the road mortality rate.

taken to" [63], p.28. The coefficients of the emergency ambulance indicator (EAMB) and the emergency doctors (EDOC) also have the anticipated statistically significant negative sign. However, the emergency nurse's indicator (ENUR) is unexpectedly significantly correlated with higher fatality rates. This could be linked to the fact that in SSA, less attention has been customarily directed to improving the training of medical and nursing staff to deal with seriously injured or diseased persons [9]. Another possible reason is the insufficient training of emergency care personnel and the inappropriate equipment in the hospitals [3,11].

6. Conclusions and recommendations

Policies aimed at reducing road death toll in Sub-Saharan Africa have been traditionally directed towards crash prevention, but the reality is that these incidents still happen. Decision-makers must therefore be prepared to dampen the drawbacks of road accidents and ameliorate the quality of life of the resulting injured. Post-crash medical care plays a key role in achieving these goals.

This paper evaluates the impact of post-crash care on road mortality in Sub-Saharan Africa. The data are estimated using a panel Bayesian normal linear regression with normally distributed non-informative priors. The post-crash care system is represented by the estimated share of seriously injured transported by ambulance, and three binary variables indicating the existence of emergency access telephone services and emergency training for doctors and nurses. The findings suggest a negative correlation between the road mortality rate and the estimated share of seriously injured transported by ambulance, the emergency access telephone services and the emergency training for doctors. This negative effect suggests that these components of the emergency care system are effective in reducing road mortality. However, a positive relation is unexpectedly observed for the emergency training for nurses.

Other factors which significantly increase the road death toll are the Gross Domestic Product per capita and populations in the age range 15–64 years while the length of the road network and life expectancy are, on the contrary, linked to decreasing fatality rates.

However, this study has some limitations. Firstly, three of the four variables of interest are indicator variables. They could have given more weight to the estimates where they quantitative measures such as densities. A further investigation of the relationship between post-crash care and traffic fatalities is suggested when such data become available because the emergency care system should be a top priority within the whole health sector research in order to confirm its prominence to effectively decrease the road death toll. Secondly, the quality of the data still requires improvements. In most of the Sub-Saharan African countries, data about road accidents are collected by the national traffic police. Assessing these data, Bhalla et al. [28] reported a dramatic underreporting of the death toll mainly in poor regions. Also, hospital databases barely cover national populations; this introduces uncertainty in the derived estimates. Nevertheless, the adjustment by the World Health Organization is an appropriate way of reducing the underreporting bias. Lastly, the study uses aggregate data which, though capturing the effects of broader policies, ignore country-specific heterogeneous effects on fatalities.

A corollary of the just-mentioned limitations is the need for the Sub-Saharan African countries to establish national continuous, systematic and viable road safety data collection systems as suggested in many studies such as [1,4,6,28,64–67]. Several national traffic safety agencies fail to create and/or regularly update their crash databases [1,4,64,65]. Overcoming these shortcomings is a key step to grapple with the magnitude of road tragedy and design policies that aim to substantially reduce road accidents and the resulting fatalities. Therefore, actions should be continually oriented towards the implementation of complete hospital-based injury monitoring systems and the amelioration of police data collection systems. Finally, as suggested by [68], the data collected from these systems should be appropriately coded, treated, examined in computerized database systems and imparted to the relevant stakeholders.

In spite of all the limitations of the study, its findings can still provide preliminary insights to road safety planners for suitable policies aiming at reducing traffic fatalities in Sub-Saharan Africa.

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Conflicts of interest

None declared.

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