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# Effects of Economic Development on Road Insecurity: Empirical Evidence for Senegal

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**Abstract** This article analyzes the effects of economic growth on road insecurity measured by the number of deaths due to road accidents in Senegal during the period 2000-2021. To do this, we used the multiple linear regression method applied to World Bank data. The results from our estimates show that economic growth has a significantly negative impact on road insecurity in Senegal. These results imply that a good part of the wealth created is attributed to the road safety policy, in particular to the renewal of the vehicle fleet considered too obsolete, to the construction of highways and the widening of roads for more room to maneuver in the event of danger, to the installation of traffic lights and to good training of law enforcement on new ICTs for good road surveillance.

**Keywords** Road insecurity, economic growth, multiple linear regression model, Senegal

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## Introduction

The improvement in living standards and the increase in the rate of motorization have contributed to the increase in mobility which has been accompanied by a sharp increase in the number of road accidents, thus placing the issue of road safety at the heart of theoretical debates due to its socio-economic consequences. Road insecurity linked to accidents kills more than 1.25 million people worldwide each year and also has a huge economic impact, with the loss of enormous human capital (Bloomberg, 2017).

On the economic level, road accidents due to road insecurity cost most countries 3% of their GDP and up to 5% for low- and middle-income countries according to the WHO for Africa (2016). For the World Bank (2017), the loss of revenue for countries that do not invest in road safety would amount to between 7 and 22% of GDP per capita, over a period of 24 years. The price of inaction is then extremely heavy in terms of health, with hundreds of thousands of injuries and deaths recorded each year worldwide, but also on the economy of countries, through a decrease in productivity and growth prospects.

In Senegal, the same observation was noted with nearly 27,000 people victims of accidents on public roads each year, of which 11,000 are recorded in Dakar, its capital. Traffic accidents represent 63.17% of all types of accidents (WHO, 2022). According to the Ministry in charge of Road Infrastructure and Land Transport, 7% of road accidents are due to the condition of vehicles and 90% to human behavior, including the speed factor which plays an extremely important role. As proof, on January 2023, two speeding buses collided, which resulted in 39 deaths.

Thus, although it is true that in 2017 the road transport sector contributed 2.1% of the GDP, all this wealth created is, however, almost wiped out by road accidents (ANSD, 2019). Indeed, the National Road Safety Agency estimates that the country loses around 2% of its GDP, or 163 billion FCFA due to accidents on public roads, a loss that could have been allocated to key sectors such as health, education, training, etc. In addition, we can mention the trauma, disabilities and reduced productivity due to road accidents which will further delay the country's development. This sufficiently proves the need, even the urgency, to combat road insecurity in order to significantly reduce the frequency of road accidents, the consequences of which are disastrous on a socio-economic level.

Furthermore, the issue of road safety has generally been addressed in the fields of transport, economics and health. Indeed, economists and road transport managers seek to establish the relationship between the reduction of road accidents and the growth of national income as measured by GDP parameters. Thus, they consider national road safety interventions as an economic investment. As for public health actors, they focus on health promotion, prevention of road accidents and deaths, as well as reducing their health and social burden. These two analytical perspectives inform and complement each other, although they each apply a different methodology for measuring the economic impact. On a theoretical level, while some economists have been interested in the economic impact of road accidents (Bhavan, 2019; Gorea, 2016; Jagnoor et al., 2015; Wang, Quddus and Ison, 2009; Damien, 1994), other researchers have focused their research on the effects of economic growth on road safety. Thus, some researchers (Akinyemi, 2019; Bloomberg, 2017; He et al. 2015; Law and Noland, 2011) confirm, in their studies, that economic growth makes it possible to improve the condition of road infrastructure (construction of highways, widening of roads, etc.) but also to effectively renew car parking and consequently, drastically reduce road accidents. According to these researchers, the dynamics of the economy puts transport actors and particularly drivers in good conditions through the revaluation of salaries and the circulation of new vehicles on roads in good condition. On the other hand, other researchers (Bougueroua and Carns, 2018; Wiebe et al., 2016; Yusuff, 2015) find the opposite by showing that economic growth worsens road insecurity by causing many more road accidents.

These debates in the economic literature show that the relationship between economic development and road safety remains relevant, thus justifying this research. To this end, we will try to answer the following question: what are the effects of economic growth on fatal road accidents?

The interest in answering this problem for the specific case of Senegal is guided by two main reasons. On the one hand, Senegal records an average of 27,000 people who are victims of accidents on public roads, causing 664 deaths each year in a context where the State of Senegal has undertaken extensive security policies (construction of toll highways, renewal of car parks, implementation of the points-based license, etc.) thanks to the dynamism of its economy over the last two decades. On the other hand, road accidents make the State of Senegal lose around 2% of its GDP despite the efforts made in terms of road safety, according to the Ministry in charge of road transport, WHO (2021) and PWA (2021).

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The general objective of this article is to analyze the effects of economic growth on road safety in Senegal. Specifically, it is a question of first identifying the determinants (microeconomics and macroeconomics) of road accidents in Senegal, then assessing the impact of economic growth on the reduction of fatal road accidents.

The remainder of the article will be devoted to the literature review (1), the presentation of the methodology and data (2) and the interpretation of the results from the econometric estimations (3).

## 1. Literature review

The debates on the correlation between economic development and road safety have been active for a long time, notably with the work of Peltzman (1975). By studying the way in which income can influence driving behavior and, consequently, the risk of accident, he argues that increasing income leads to an increased demand for intense driving. Since then, a vast literature has been devoted to the identification of the structural determinants (economic growth, unemployment, health expenditure, investments, etc.) of road safety.

Indeed, different approaches such as the number of fatal accidents, the number of people killed and seriously injured, the number of deaths per motor vehicle mileage, etc., have been used to measure road safety (Forsman, 2012). When it comes to measuring economic development, a number of different variables are used, but most of the time, only one variable per study is used. This is probably because the variables are highly correlated, which can lead to model fitting problems. The most common measure of economic development in the reviewed road safety literature is the change in GDP (Akinyemi, 2020; Bougueroua and Carnis, 2016; Hu et al., 2008; Noland, 2005; Gullon, 2002; Al-Alawi et al., 1996).

Akinyemi (2020) examined the relationship between economic development and road traffic accidents (fatalities and injuries) in Nigeria. He used the ARDL approach of cointegration to determine the short-run and long-run effects of economic development on road safety over a 26-year period (1991 – 2016). The analysis was conducted using annual data related to gross domestic product per capita (GDP) and unemployment rate for the level of economic development, as well as the number of road traffic accidents, fatalities and injuries, indicators of road safety. The results showed that in the long run, accidents and fatalities decrease while injuries increase with GDP. In the short run, fatalities decrease with GDP, but the negative impact of GDP on injuries manifests itself after a three-year lag. GDP had a significant effect on accidents, fatalities and injuries in the long run. Bougueroua and Carnis (2016) applied a cointegration approach and a vector error correction model to examine the short- and long-run relationship between the number of road accidents, fuel consumption, and GDP per capita over the period 1970–2013 in Algeria. The results of their study revealed that GDP per capita had a positive influence on the number of road accidents in both the short and long term. Using the group average estimator of common correlation effects (Pesaran) technique, Antoniou et al. (2016) analyzed the time series of the number of deaths and GDP in 30 European countries over the period 1975–2012. They concluded that the average value of the long-run elasticity was 0.63 and was significantly different from zero for 10 countries.

He et al. (2015) used a multivariate fixed-effects model to examine the relationship between gross regional product (GRP), road traffic fatalities (RTF), and crash fatality rate (CFR) in Russia for the period 2004–2011. Their results showed that RTF and CFR decreased monotonically as GRP per capita increased across all 66 regions.

Law (2015) applied a fixed-effect binomial regression analysis to panel data from 90 countries over the period 1963–2009 to study the Kuznet curve relationship between non-fatal road traffic accidents and per capita income. The results showed an inverted U-shaped relationship in which road traffic fatalities increased with increasing per capita income at lower income levels but decreased when it exceeded a threshold.

The study by Wiebe et al. (2016) analyzed the causal relationship between GDP and road traffic fatalities in Botswana and Zambia using Dickey-Fuller test, vector autoregressive analysis and Granger causality. The results suggest that GDP growth led to an increase in road traffic fatality rate. In Zambia, annual changes in GDP led to an increase in the fatality rate after three years. Yusuff (2015) in his study found an inverse relationship between road traffic fatalities and economic growth in Nigeria. Furthermore, according to the long-run elasticity coefficient of Model 2, it is revealed that there is an increase in per capita health expenditure of 0.87% associated with every 1% increase in total road traffic fatalities. Model 3 specifies that an increase of 0.45% and 3.5% in total government expenditure is associated with a 1% increase in the fatality index and the injury index, respectively.

Bishai et al. (2006) studied the influence of GDP per capita on road safety in 41 countries grouped into “low-income countries” and “rich countries”. They found that a 10% increase in GDP in a low-income country would lead to a 7.9%

increase in accidents (4.7% in injuries and 3.2% in deaths). Conversely, an increase in GDP in the case of the richest countries could be associated with a reduction in the number of deaths, but not in the number of accidents or injuries. Subsequently, Gaygisiz (2009) added GDP per capita, unemployment, the Gini index and a series of variables related to cultural characteristics to the economic indicators already mentioned. This author reached different qualitative associations. For example, countries with high accident rates were associated with greater acceptance of social inequalities, while countries with low rates showed greater individualism. A relationship also emerged between favorable economic conditions (high per capita income, low unemployment, and low-income inequality) and better road safety.

Although there is an abundant literature on the impact of economic development on road safety, the evidence of this relationship in developing countries and particularly in sub-Saharan Africa is, however, limited; hence the importance of this empirical research for the case of Senegal.

## 2. Methodology and data

In this article, two models were used to first identify the explanatory factors of accidents and then assess the impact of economic growth on the reduction of fatal road accidents in Senegal.

### 2.1 Model 1: Generalized ordered log it regression

#### 2.1.1 Model presentation

The Ordinal Regression Model follows the assumption that the effect of each predictor is the same in all categories of the ordinal response variable. This restriction is called the proportional odds assumption or the parallel lines assumption which results from the assumption that the coefficient vector $\beta$ is the same for the $m-1$ logit equations.

$ln\,\Omega_{\leq j|>j}(x) = C_j - x\beta$ ; où$\Omega_{\leq j|>j}(x) = Prob(y \leq j|x)/Prob(y > j|x)$.

This assumption is strict and is often violated in real data analysis since the test score is strongly affected by the sample size and the number of covariate models, for example by including continuous covariates as predictors (Allison, 1999; Menard, 2001 and Xing Liu, 2015).

To address this issue, the best option is to fit a partial proportional odds model such as the generalized ordinal logit model (Williams, 2006 and Xing Liu, 2015). In the partial proportional odds model, not all predictor variables violate the proportional odds assumption, so the effects of predictors that violate the assumption are allowed to vary across categories. The generalized ordinal logit model can be considered as a special case of the partial proportional odds model, it allows the effect of each explanatory variable to vary, that is, for this model, each coefficient $\beta$ can vary for each of the $m-1$ logit equations, that's to say:

$ln\,\Omega_{\leq j|>j}(x) = C_j - x\beta_j$ ; for $j = 1, \ldots, m-1$ ; where the predicted probabilities are calculated as follows:

$$Prob(y = 1|x) = \frac{e^{(C_1 - x\beta_1)}}{1 + e^{(C_1 - x\beta_1)}}$$

$$Prob(y = j|x) = \frac{e^{(C_j - x\beta_j)}}{1+e^{(C_j - x\beta_j)}} - \frac{e^{(C_{j-1} - x\beta_{j-1})}}{1+e^{(C_{j-1} - x\beta_{j-1})}} \text{ ; for } j = 1, \ldots, m-1$$

$$Prob(y = m|x) = 1 - \frac{e^{(C_{j-1} - x\beta_{j-1})}}{1 + e^{(C_{j-1} - x\beta_{j-1})}}$$

Thus, according to Long and Freese (2014), for the generalized ordered log it model, there is no formal constraint that excludes negative predicted probabilities. Moreover, as these latter authors have pointed out, the generalized ordered log it model is not an ordinal regression model because, like the multinomial logit model, it does not necessarily make predictions that maintain the ordinality of the results.

#### 2.1.2 Choice of variables and data sources

The selection of variables that could explain the severity of road accidents in Senegal was done firstly, on the basis of the literature. Thus, all the variables deemed relevant in the literature for the study of the severity of the accident and present in our database are selected. Secondly, we carried out chi-square independence tests between the response variable and all the selected variables to keep only those that are statistically linked to the dependent variable: these are then the candidate variables. Then, the inter-correlations between candidate variables are analyzed, in order to keep only the variables with a low inter-correlation rate, which will then constitute our potential explanatory variables. Finally, using the stepwise downward method and based on the AIC criterion for model comparison, we kept 13 variables in the ordered logit model.

**Table 1: List of the thirteen (13) explanatory variables of the study**

| Variable | Label | Code | Expectedsign |
|---|---|---|---|
| Driver Gender | Driver Gender (Male or Female) | driv-gender | (+/-) |
| Age range | Driver age range (Under 25years, 25-34years, 35-44years, 44-54years et 55years or over) | age range | (-) |
| Driving whileintoxicated | Accident occurring while driving under the influence of alcohol or not | driver_alcoh | (+) |
| Speeding | Accident occurring while driving at excessive speed or not | exces_speed | (+) |
| License age | License age (Under 5 years, 5-10 years, over 10 years and No License) | age_license | (-) |
| Vehicle type | Type of vehicle or means of transport involved in the accident (Moped, Sedan, Van, Bus and Truck). | vehic_type | (+/-) |
| Vehicle age | Age range of the vehicle involved in the accident (less than 5 years, 5-10 years and more than 10 years) | vehic _age | (+) |
| urban area/country side | Place where the accident occurred (urban area or countryside) | urbar_counsid | (+/-) |
| Brightness | Lighting level of the area where the accident occurred (low, medium and high). | brightness | (-) |
| Time slot | Time slot of the accident (00h-06h, 06h-12h, 12h-18h et 18h-00h) | time slot | (+/-) |
| Region | Population density (average populated region, sparsely populated region and more populated region) | region | (+) |
| Road type | Traffic nature of the road where the accident occurs (slow traffic road, fast traffic road and faster traffic road) | type_road | (+) |
| Number of vehiclesinvolved | Number of vehicles involved in the accident (one vehicle, two vehicles and more than three vehicles) | nb_veh_invol | (+) |

The data used to capture the different variables chosen come from the Financial Services Quality Observatory of the Ministry in charge of the Economy of Senegal.

### 2.2 Multiple Linear Regression Model

In this study, we seek to directly explain road accident mortality from GDP and other macroeconomic indicators present in our database in Senegal. Since our endogenous variables are all quantitative, then the most appropriate method is the linear regression model.

#### 2.2.1 Theoretical reminder of the multiple linear regression model

Linear regression is a parameter estimation method, generally used when the phenomenon studied is continuous in nature and the explanatory variables.

In general, regression models are built with the aim of explaining (or predicting) the variance of a phenomenon (dependent variable) using a combination of explanatory factors (independent variables).

In the case of multiple linear regression, the dependent variable is always a continuous variable while the independent variables can be continuous or categorical.

Linear regression is said to be multiple when the model is composed of at least two independent variables.

In general, statistical models are presented as follows:

$$Yi = a_0 + a_1 x_{i,1} + \cdots + a_p x_{i,p} + \epsilon_i$$

The aim here is to estimate the values of the $(p + 1)$parameters $(a_0, a_1 \ldots, a_p)$from a sample of $n$ observations (often called individuals). $i = 1, \ldots, n$Corresponds to the number of observations; $Y_i$is the $i^{th}$observation of the variable $Y$; $x_{i,j}$is the $i^{th}$ observation of the $j^{th}$variable; $\varepsilon_i$is the model error, it summarizes the missing information that would allow the values of $Y$ to be explained linearly using the $p$ variables $X_j$. The objective is to estimate the values of the coefficients $(a_0, a_1, \ldots, a_p)$from a sample of data using the ordinary least squares method.

### Matrix notation

To simplify the notations, we often find a matrix writing of the model in the literature.

$$Y = Xa + \varepsilon$$

$Y \rightarrow (n, 1)$ ; $X \rightarrow (n, p + 1)$ ; $a \rightarrow (p + 1, 1)$ and $\varepsilon \rightarrow (n, 1)$

The matrix X of size $(n, p + 1)$ contains all the observations on the exogenous, with a first column formed by the value1 indicating that we integrate the constant $a_0$ in the equation, it is given by:

$$\begin{pmatrix} 1 & x_{1,1} & \cdots & x_{1,p} \\ 1 & x_{2,1} & \cdots & x_{2,p} \\ \vdots & & & \\ 1 & x_{n,1} & \cdots & x_{n,p} \end{pmatrix}$$

### 2.2.2 Estimation by the ordinary least squares (OLS) method

Minimization of the sum of squared errors: the principle consists of finding the coefficients which make it possible to minimize the following quantity.

$$S = \sum_{i=1}^{n} \varepsilon_i^2$$

Or $\varepsilon_i^2 = [y_i - (a_0 + a_1 x_{i,1} + \cdots + a_p x_{i,p}]^2$

We again go through the partial derivatives which we cancel to obtain the following p + 1 normal equations.

$$\begin{cases} \frac{\partial S}{\partial a_0} = 0 \\ \vdots \\ \frac{\partial S}{\partial a_p} = 0 \end{cases} \Leftrightarrow \begin{cases} -2\sum_i \varepsilon_i = 0 \\ \vdots \\ -2\sum_i x_{i,p} \times \varepsilon_i = 0 \end{cases}$$

$$\Leftrightarrow \begin{cases} a_0 + a_1\bar{x}_1 + \cdots + a_p\bar{x}_p = \bar{y} \\ \vdots \\ a_0\sum_i x_{i,p} + a_1\sum_i x_{i,1}x_{i,p} + \cdots + a_p\sum_i x_{i,p}x_{i,p} = x_{i,p}y_i \end{cases}$$

We have (p + 1) Equations (p + 1) unknown. It is now a question of extracting the estimates $(\hat{a}_0, \hat{a}_1, \ldots \hat{a}_p)$. Given the difficulties in manipulating these equations, it is convenient to use matrix notations

### Matrix notation

With matrix notation, we can produce a condensed notation. Let ε be the vector of errors, with $\varepsilon' = (\varepsilon_1, \ldots, \varepsilon_n)$. The sum of the squares of the errors becomes:

$$\sum_{i}^{n} \varepsilon_i^2 = \varepsilon'$$

Which leads to developing:

$\varepsilon'\varepsilon = (Y - Xa)'(Y - Xa)$

$= Y'Y - Y'Xa - a'X'Y + a'X'Xa$

$= Y'Y - 2a'X'Y + a'X'Xa$

$S = Y'Y - 2a'X'Y + a'X'Xa$

Cancelling the matrix derivation gives:

$$\frac{\partial S}{\partial a} = -2(X'Y) + 2(X'X)a$$

The ordinary least squares (OLS) estimator of the model coefficients is written as:

$$\hat{a} = (X'X)^{-1}X'Y$$

### 2.2.3 Model validation

#### Global significance test of the regression

The overall significance test consists of checking whether the model, taken as a whole, is relevant. The null hypothesis corresponds to the situation where none of the exogenous factors provide useful information in explaining Y, i.e. the model is useless. The test is written as:

$$\begin{cases} H_0 : a_1 = a_2 = \cdots = a_p = 0 \\ H_1 : \exists j \,/\, a_j \neq 0 \end{cases}$$

Testing the significance of a coefficient

After establishing the overall significance of the regression, we must evaluate the relevance of the variables taken individually. Since $i \equiv N(0, \sigma\varepsilon)$, we show that

$$\frac{\hat{a}_j - a}{\hat{\sigma}_{\hat{a}_j}} \equiv \mathcal{T}(n - p - 1)$$

The principle of the test is as follows:

$$\begin{cases} H_0 : a_j = 0 \\ H_1 : a_j \neq 0 \end{cases}$$

Hypothesis $H_0$ implies that the removal of the variable $X_j$ is possibly possible. In other words, the contribution of $X_j$in the explanation of $Y$ is not significant compared to the others. Be careful, however, because collinearity problems can sometimes disrupt the results.

The test statistic is written as:

$$t_{\widehat{a_j}} = \frac{\widehat{a_j}}{\widehat{\sigma_j}}$$

And the critical region for a given risk α, the test being bilateral:

$$R.C.: \left|t_{\widehat{a_j}}\right| > t_{1-\frac{\alpha}{2}}(n - p - 1)$$

### 2.2.4 Choice of variables and data sources

Considering GDP per capita as an endogenous variable, the correlation matrix gives the following results.

**Table 2: correlation of variables**

| Matrix of correlations | | | | | | |
|---|---|---|---|---|---|---|
| Variables | Mortality due to road accidents | GDP per capita | FCE (% GPD) | FCEG | Health expenditure (%GPD) | FDI (% GDP) |
| Mortality due to road accidents (pour 100 000 habitants) | 1.000 | | | | | |
| GDP per capita (dollars) | -0.150 | 1.000 | | | | |
| Final consumption expenditure (% GDP) | -0.449 | 0.182 | 1.00 | | | |
| Final consumption expenditure of general government | 0.491 | -0.178 | -0.096 | 1.000 | | |
| Health expenditure (%GPD) | 0.894 | -0.168 | -0.381 | -0.757 | 1.000 | |
| FDI (% GPD) | 0.627 | -0.032 | -0.189 | -0.729 | 0.086 | 1.000 |

Source: WDI, authors' calculations

From the correlation matrix, we can predict the direction of the effect of each exogenous variable on fatal road accidents (see expected sign column of the table below).

**Table 3: List of study variables, with GDP per capita as the endogenous variable**

| Variable | Expectedsign |
|---|---|
| Mortality due to road accidents (pour 100 000 habitants) | (-) |
| GDP per capita (dollars) | |
| Health expenditure (%GPD) | (-) |
| Final consumption expenditure (% GDP) | (-) |
| Foreign direct investment (% GDP) | (+) |
| Final consumption expenditure of general government | (+) |

Source: WDI, authors' calculations

The data used in this research come from the WDI/World Bank database. These are time series data spanning thirty-two (32) years (from 1990 to 2021) and provide information on macroeconomic indicators for Senegal, namely road traffic accident mortality (per 100,000 inhabitants), GDP per capita (in dollars), current health expenditure (% of GDP), final consumption expenditure (% of GDP), foreign direct investment (% of GDP) and final consumption of general government.

## 3. Analysis of the results

### 3.1 Analysis of the results of the estimation of model 1

Since we have an ordinal qualitative response variable, then in a first step, we applied the ordered logit model (ologit) which, unlike models for nominal variables (multinomial models), is a very restrictive proportional odds model that is based on the parallel lines hypothesis; that is, the effect of an explanatory variable must be identical

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between all the different observed categories of the dependent variable (Long and Freese, 2014). For the selection of the best model, we used the stepwise downward method based on the model comparison criterion: AIC. After comparing 36 models, we end up maintaining the model with 10 explanatory variables: *age_range, exces_speed, vehicle_type, age_vehicle, urbar_counsid, region, time_ slot, type_road, brightness, nb_veh_invol,* instead of the 34 initial variables with an AIC equal to 11600. The results of the ordered logit model finally retained are presented in the following.

**Table 4: Results of the estimation of model 1**

| **Variables** | **Coefficients** |
|---|---|
| Age range | 0,025*<br>(0,043) |
| Speeding | 0,159***<br>(0,604) |
| Type of vehicle | 0,021***<br>(-0,196) |
| Age of vehicle | 0,022***<br>(0,116) |
| Urban area/countryside | 0,085***<br>(1,097) |
| Region | 0,051***<br>(0,277) |
| Time slot | 0,031***<br>(-0,133) |
| Type de road | 0,052***<br>(0,501) |
| Brightness | 0,036***<br>(0,258) |
| Number of vehiclesinvolved | 0,061***<br>(-1,441) |
| | |
| Number of obs | 6609 |
| Wald chi2(11) | 1240,23 |
| Prob > chi2 | 0,000 |
| Pseudo R2 | 0,141 |

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Source : OQSF du Ministère de l'Economie et des Finances, Autours calculassions, Stata software output

The p-value of the overall model (Prob $> chi2) = 0.000 < 0.05$ indicates a strong overall significance of the model. On the other hand, we have a pseudo $R^2 = 0{,}1410 < 0{,}20$ so the model is poorly adjusted or inadequate to the data. However, pseudo $R^2$values between 0.20 and 0.40 are to be considered satisfactory.

The line entitled "All" of the results of the Brant test shows that the parallel regression hypothesis is not verified. Indeed, for this test, a significant p-value (≤ 0.05) proves that the parallel lines hypothesis has been violated (See column: (p>chi2) ≤ 0.05 of Appendix 1).

Other tests of the parallel regression hypothesis with the command "oparallel, ic" which gives at the same time the criteria of comparisons of models such as the AIC and the BIC were also carried out (see appendices 3 & 4).

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Thus, the results obtained made it possible to group the determinants of fatal road accidents into three (3) categories.

- **Driver characteristics**

According to gender, men are 6.9% more likely to be involved in serious accidents (with bodily injuries) than women. As for the age of the driver, motorists aged between 25 and 34 are less likely to be involved in accidents with bodily injuries (7.1%) and this trend is observed as age increases. Regarding speeding, it generates a risk of causing considerable bodily injuries (13.7%). According to the results obtained, motorists whose license age is less than 5 years are more likely to be involved in serious accidents (1%), or even fatal accidents (1.3%) compared to drivers whose license age is more than 5 years. In addition, drivers without a license, most of whom are moped riders (see Appendix 3), are at greater risk of causing serious accidents (with bodily injury (28.9%). However, the driver's state of intoxication has no effect on fatal road accidents.

- **Vehicle characteristics**

For the type of vehicle, mopeds are at greater risk (7.8%) of causing more serious or even fatal accidents than sedan vehicles. Regarding the age of the vehicle, vehicles aged between 5 and 10 years seem to have a greater risk of causing serious (1.5%) or very serious (2%) accidents and this trend is observed as the vehicle ages.

- **Road characteristics and its environment**

Depending on the location of the accident (urban area or countryside), very serious (fatal) accidents are 17.4% more likely to have occurred in the countryside than in an urban area. Regarding the light level, hours of low light (usually night) have a 5.2% higher risk of very serious accidents than hours of average light (dawn or dusk). The accident time slot factor also shows that very serious accidents appear to have a 2.9% higher risk of occurring between 00:00-06:00 than between 06:00-12:00.

According to the results from the model estimation, the region of occurrence showed that very serious accidents, i.e. fatal accidents, are 2.7% more likely to have occurred in medium-populated regions than in sparsely populated regions. On the other hand, very serious accidents are 4.2% less likely to have occurred in highly populated regions than in sparsely populated regions. For the traffic nature, roads with faster traffic (RN and motorways) seem to record the most fatal accidents (4.5%) than those with slow traffic (laterite, track and road under construction). Regarding the number of vehicles involved, accidents involving more than 2 vehicles (pile-up) are 15.8% more likely to be very serious (certainly with fatalities) than those involving a single vehicle.

### 3.2 Analysis of the results of the estimation of model 2

After cleaning the database by treating the missing data and outliers, a brief descriptive analysis is carried out on the indicators to have an overview of the latter.

**Table 5: Descriptive analysis**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Mortality due to road accidents (pour 100 000 habitants) | 32 | 13.769 | 9.184 | 1 | 24.8 |
| Final consumption expenditure (% GDP) (FCE) | 32 | 90.836 | 4.32 | 82.323 | 98.138 |
| Foreign direct investment (% GDP) | 32 | 1.697 | 1.051 | -0.104 | 4.553 |
| GDP per Capita (dollars) | 32 | 1077.169 | 320.538 | 598.145 | 1636.893 |
| Expenditure health | 32 | 8.092 | 5.606 | 1 | 20 |
| Final consumption expenditure of general government (FCEGG) | 32 | 13.654 | 1.359 | 11.404 | 17.088 |

Furthermore, we will consider GDP per capita as an endogenous variable that also captures the economy of Senegal and other variables such as Public Expenditure, the road accident mortality rate, final consumption expenditure and gross fixed capital formation being the explanatory variables.

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Once the model validation tests have been carried out and the fundamental assumptions validated, we then move on to interpreting the results recorded in the table below.

**Table 6: Results of the estimation of model 2**

| **Variables** | **Coefficients** |
|---|---|
| FDI | -1.63<br>(1.20) |
| FCEGG | 1.94**<br>(0.72) |
| Exphealth | -0.62***<br>(0.20) |
| GDP per Capita | -0.00***<br>(0.00) |
| FCE | -0.38<br>(0.30) |
| Constante | 91.35**<br>(35.74) |
| Observations<br>Prob>Khi2 | 32<br>0.0000 |
| R-squared<br>R2 ajustée | 0.73<br>0.68 |

The explanatory variables used explain more than 70% of the variability of the mortality rate due to road accidents. Except for FDI, all other exogenous variables have a significant effect at the 1% threshold on road accident mortality in Senegal. On the one hand, we have the final consumption expenditure of public administrations (DCFAP) which have a negative impact on the reduction of road accident mortality in Senegal. In other words, an increase of one unit of DCFAP leads to an increase of 1.94 in the road accident mortality rate in Senegal. Conversely, current health expenditure (DCS), GDP per capita (GDP) and final consumption expenditure have a positive effect on the reduction of road accident mortality in Senegal. Indeed, an increase of one unit of DCS would allow a reduction of 62% of the road accident mortality rate in Senegal. Similarly, a growth of one unit of GDP per capita would lead to a reduction of 0.0095% or 9.5/100,000 of the road accident mortality rate in Senegal. Finally, an increase of one unit of final consumption expenditure would reduce the road accident mortality rate in Senegal by 38%.

Furthermore, the results from the estimates seem to indicate that the country's economic development helps reduce fatal road accidents. This confirms the work of Akinyemi (2019), Bloomberg (2017), He et al. (2015), Law and Noland (2011) which reveals that part of the wealth created and invested in road safety could drastically reduce road accidents.

Thus, the results found in this research perfectly describe the situation prevailing in Senegal. The proof is that Senegal has invested in combating road accidents by implementing various measures. These measures include the introduction of the points-based license system, which forces drivers to drive carefully at the risk of losing their license in the event of repeated offenses. Added to this is the pointing by the gendarmes on national roads to ensure the control of vehicles and drivers.

In addition, these measures are accompanied by a vast road infrastructure construction program that the State of Senegal has undertaken since 2000, such as toll highways that have significantly reduced mortality due to road accidents. Examples include the Ila-Touba, Thiès-Mbour and Mbour-Kaolack highways serving as major arteries between the interior and the coast of the country; the Foundiougne Bridge that spans the Saloum River, connecting the North and the South; and the Dakar-Saint Louis highway, which is well advanced in its construction. In addition, the State of Senegal has begun a few years ago to renew the car park, which is considered by road transport experts to be too dilapidated. In the capital (Dakar), there are fewer and fewer fatal accidents due to the very heavy investments in infrastructure (flyovers, Malick Sy toll highways, VDN, Soumbédioune tunnel, Corniche Ouest, etc.) that the various successive governments have been able to undertake from 2000 to the present day. However, it is important to put the results of the estimates obtained into perspective since fatal accidents are sometimes frequent despite the will and efforts of the State and especially during religious events when the behavior of drivers is often singled out. The deadly accident at the height of Sikilo in the Kaffrine region (central Senegal) in 2023 (which is not included in our econometric estimates) is proof of an act of indiscipline on the part of the drivers of the two buses since the collision caused 39 deaths out of the 139 passengers. Since then, with the new measures taken by the state authorities such as the ban on public transport vehicles (buses, coaches, mini coaches) from circulating from 10 p.m. to 5 a.m., the removal of luggage racks, the reinforcement of road checks, no such fatal accidents have been recorded.

## Conclusion and recommendations

This article analyzes the effects of fatal road accidents on the economy of Senegal. More specifically, it aims at identifying the different explanatory factors of fatal road accidents and econometrically test the effects of the latter on economic growth. Based on the ordered logit model, which allows us to analyze the explanatory factors of road accidents in Senegal, and that of multiple linear regression, our results show that economic growth has a positive and significant impact on the reduction of fatal road accidents in Senegal over the period 2000-2021.

The economic policy implications that should arise from this research must be oriented towards road safety policy, which should be based on a thorough diagnosis of the current situation. If the State of Senegal wishes to significantly reduce accidents, it must allocate part of the wealth created to road safety to deal with certain factors that frequently cause accidents by first reviewing the standards for road construction due to their narrowness which gives no room for maneuver to drivers and particularly heavy vehicles (trucks, buses, coaches, etc.). Added to this is the renewal of the vehicle fleet which is considered too dilapidated. Indeed, several vehicles continue to circulate even though they no longer comply with road safety standards. And finally, it must review the driver control policy which has many flaws. Indeed, the behavior of drivers is the main source of accidents since, when driving, they are often tired or intoxicated and especially during periods of religious events when there are more fatal accidents. In summary, the government, policy makers, road safety agencies, motorists and motorcyclists should invest in road infrastructure, traffic enforcement and safety measures that will reduce injuries and especially during religious events where responsibilities are fully shared.

The implication of this finding will open new avenues for future research and may also be useful to experts and policy makers when comparing the economic effects related to road accidents.

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## Appendices

**Appendix 1: Results of the estimation of the last ordered logit model retained**

| | | |
|---|---|---|
| Orderedlogisticregression | Number of obs | 6609 |
| | Wald chi2(11) | 1240,23 |
| | Prob > chi2 | 0,000 |
| Log pseudolikelihood = -5787.9978 | Pseudo R2 | 0,141 |

| All | Coefficient | Robust std. err. | z | P>z | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| age _ range | 0,043 | 0,025 | 1,730 | 0,084 | -0,006 | 0,091 |
| exces_speed | 0,604 | 0,159 | 3,810 | 0,000 | 0,293 | 0,914 |
| vehic_type | -0,196 | 0,021 | -9,470 | 0,000 | -0,237 | -0,156 |
| vehic _ age | 0,116 | 0,022 | 5,370 | 0,000 | 0,074 | 0,159 |
| urbar_counsid | 1,097 | 0,085 | 12,900 | 0,000 | 0,931 | 1,264 |
| region | 0,277 | 0,051 | 5,410 | 0,000 | 0,177 | 0,377 |
| time_slot | -0,133 | 0,031 | -4,300 | 0,000 | -0,194 | -0,072 |
| road _ type | 0,501 | 0,052 | 9,720 | 0,000 | 0,400 | 0,602 |
| brighness | 0,258 | 0,036 | 7,260 | 0,000 | 0,188 | 0,328 |
| nb_veh_invol | -1,441 | 0,061 | -23,600 | 0,000 | -1,561 | -1,322 |
| /cut1 | 0,368 | 0,214 | | | -0,051 | 0,787 |
| /cut2 | 2,170 | 0,209 | | | 1,760 | 2,579 |

Source: MEFP OQSF, author's calculations, Stata software output

**Appendix 2: Brant test of the parallel regression hypothesis**

| | chi2 | p>chi2 | df |
|---|---|---|---|
| All | 3329,27 | 0,000 | 10 |
| age _ range | 0,07 | 0,792 | 1 |
| exces_speed | 1,18 | 0,278 | 1 |
| vehic_type | 10,98 | 0,001 | 1 |
| vehic _ age | 7,44 | 0,006 | 1 |
| urbar_counsid | 19,26 | 0,000 | 1 |
| region | 5,52 | 0,019 | 1 |
| time_slot | 2,80 | 0,094 | 1 |
| road _ type | 3,80 | 0,051 | 1 |
| brighness | 0,49 | 0,482 | 1 |
| nb_veh_invol | 2672,49 | 0,000 | 1 |

**Appendix 3: Brant test of the parallel regression hypothesis**

| Test title | Chi2 | df | P>Chi2 |
|---|---|---|---|
| Wolfe Gould | 2459 | 10 | 0,000 |
| Brant | 3329 | 10 | 0,000 |
| Score | 2866 | 10 | 0,000 |
| Likelihood ratio | 1255 | 10 | 0,000 |
| Wald | 2195 | 10 | 0,000 |

Appendix 4: Information criteria

| Title | Ologit | Gologit | difference |
|---|---|---|---|
| AIC | 11600 | 10364,62 | 1235,38 |
| BIC | 11681,55 | 10514,14 | 1167,41 |

We still have a p-value (p>chi2) ≤ 0.05, confirming the violation of the parallel slopes hypothesis.

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**Appendix 5: License age by vehicle type**

| | Vehicle type | | | | | |
|---|---|---|---|---|---|---|
| license age | moped | sedan | van | Bus | truck | total |
| less than 5 years | 43 | 779 | 181 | 255 | 311 | 1569 |
| 5-10 years | 19 | 907 | 219 | 391 | 277 | 1813 |
| over 10 years | 28 | 1596 | 292 | 539 | 500 | 2955 |
| no license | 206 | 52 | 4 | 4 | 6 | 272 |
| Total | 296 | 3334 | 696 | 1189 | 1094 | 6609 |