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Investigating the Asymmetric Effects of Economic and Demographic Factors on Traffic Accident Severity – Evidence from a Nonlinear ARDL Approach

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ABSTRACT

This study adopts an innovative nonlinear autoregressive distributed lag (N-ARDL) approach and compares it with the standard ARDL and the traditional ordinary least-squared (OLS) regressions. These approaches are used to examine the long-run and dynamic relationships between the accident severity in urban Jordan cities and the following explanatory variables: proportion of population living in urban areas, GDP growth rate, total length of road networks, vehicle ownership growth rate and spaces of newly added buildings. The case study covers the period from 2004 to 2022. The standard and nonlinear ARDL estimates showed the presence of long-run co-integration between variables. Moreover, the NARDL estimates on the long- and short-run indicate a varying effect of the considered explanatory variables on accident severity at the positive and negative partial sum. In general, GDP growth positively affects accident severity in the short run. Whereas, the expansion of road length presents a positive and negative impact on the upward and downward partial sum. In contrast, the explanatory variables differed in their impact on accident severity on each side of asymmetry. The variability of the results obtained by the nonlinear ARDL model helps suggest different policies for different high and low levels of traffic safety.

KEYWORDS

traffic accident severity; ARDL model; nonlinear ARDL model; urbanization; Jordan.

1. INTRODUCTION

Urbanization has been considered to have a profound impact on the population in many aspects, among which road traffic safety. In Jordan, traffic accidents annually cause between 600 to 900 deaths and more than 13,000 injuries, approximately 70% of whom are in urban cities [1]. These numbers are considered high for a small country with less than 12 million citizens. The country also loses around 2–3% of its gross domestic product due to this global issue [2, 3].

There is a fairly extensive literature focused on identifying the direct contributing factors to road accidents [4–6]. Part of the scholars have been directed to crash sites and inspect all related conditions (i.e. vehicle, human and road conditions) [7, 8]. Other road safety research has investigated the special change in accident risk across geographic spaces [9–11]. However, these scholars were limited to a short study period and ignored the annual impact of social and economic factors on traffic safety.

Earlier evidence has linked increased road traffic accidents with the growth in population rate and motorization which accompanied economic growth, especially in less developed countries [12, 13]. In this area, several time series models have been conducted to determine the specific economic indicators influencing road traffic accidents. Scuffham (2003) applied the Structural Time Series Model to examine the changes in fatal accident patterns in New Zealand to economic conditions [14]. Oreko et al. (2017) and Twenefour et al. (2021) used the Box-Jenkins model to forecast the annual change in road accidents [15, 16]. Moreover, the

Autoregressive Integrated Moving Average (ARIMA) and seasonal ARIMA have been widely applied [17–19] to examine the changes in accident patterns in relation to economic conditions. However, these models may not be ideal for nonstationary or nonlinear series, which may lead to spurious regression.

Traffic accident data are inherently heterogeneous and may have non-linear distributions [20]. The autoregressive distributed lag (ARDL) is an econometric technique used to determine the long-run co-integration between non-stationary time series. The ARDL is more robust than the conventional time series models and performs better for small sample sizes. There is a vast empirical literature available that applies the ARDL approach to examine the relationship between different social and economic variables and traffic accidents [21, 22]. Li et al. (2020) adapted the ARDL technique to investigate the long-run and short-run impact of socioeconomic volatility in China on traffic accident indicators (i.e. crashes, injuries and fatalities) spanning from 1999 to 2018 [23]. The study found that private vehicle ownership is positively correlated with traffic fatalities. In contrast, inverse results are found by road mileage. The same approach is applied by Ageli and Zaidan (2013) [24]. Their work affirmed a strong co-integration between traffic accidents and GDP, population, registered vehicles, road miles and the number of driver's licenses. The result also presented a bi-directional Granger causality between the variables. In Nigeria, Ayodeji, Dauda and Oyelami (2020) studied the dynamic causal relationship among economic growth, motorisation and traffic accidents [25]. Both studies applied the ARDL framework to address the expected endogeneity problem and non-uniform stationarity in the data. The results confirmed that economic growth contributes to traffic accidents through increasing motorisation in Nigeria. Generally, Imran (2018) and Ali, Yaseen and Khan (2019) have also explored the nexus between traffic accidents and socioeconomic indicators in different high and low-income countries in the short- and long-run [26, 27]. Most of these studies have shown the significant impact of population growth and private car ownership on road accidents.

Other literature has used other variables to explain the annual change in road safety. Ali, Yaseen and Khan (2020) established a two-way short-run causality between traffic accidents and both rainfall and health expenditures [28]. The result showed a unidirectional causality from traffic accidents to the two variables. The two studies have also shown a positive and negative effect of rainfall and increased health expenditure on road safety, respectively. Other important variables were also found in Yaseen, Ali and Khan's (2018) work [29]. The authors found a bidirectional causality between accident deaths and foreign direct investments. The results present a reduction in road fatalities by increasing trade openness and the number of road safety research studies. Moreover, the effect of gasoline prices on traffic accident indicators in the short and long term was also studied by Akinyemi (2023) [30]. However, the previously raised literature unanimously agreed that an increase in road traffic accidents can hamper economic growth. *Table 1* gives a review of the literature that studied traffic accident series in several countries with their main conclusions.

Most of these empirical studies use the ordinary least square (OLS) regression and Granger causality test to estimate the impact of the explanatory variables on the mean of the conditional accident severity distribution, which only considers its conditional mean. It cannot describe the possible asymmetric relationship between the independent variable and the regressor. The nonlinear autoregressive distributed lag (NARDL) goes beyond the estimation of mean and variance typically found in time series analysis. The nonlinear version of the ARDL model is widely used in literature such as economics, finance, social science and ecology [31–33]. The NARDL model allows to assessment of the odds of being in the upper or lower tails of the dependent variable to check the volatility of results outside the mean.

This paper uses the asymmetric nonlinear ARDL model [34] to investigate the relationship between the accident severity in urban Jordan districts and the following explanatory variables: proportion of population living in urban areas, GDP growth rate, unemployment rate, total length of road network, vehicle ownership growth rate and areas of newly added building. The main advantage of the NARDL approach is that it captures the potential nonlinear relationship between variables by exploring the positive and negative partial sum of the series allowing for a more dynamic investigation of accident severity. Contrary to the standard linear models, the NARDL technique allows to simultaneously examine the long-run relationship with their related short-run dynamic for the high and low accident severity. Thus, this framework helps assess the strength of these relationships under different severity scenarios. Moreover, this paper also compares the nonlinear ARDL with the standard ARDL model and OLS regression.

The three main contributions of this research compared to previous work are as follows. First, this is the first time, to the best of our knowledge, that the nonlinear ARDL approach is used to study the effect of socioeconomic variables on road accident severity. In other words, this study explores the effect during different states of accident severity. That is when the severity is high (i.e. high accident risk) and low (i.e. low accident risk). Second, this work investigates the severity of accidents rather than frequency, providing a more accurate and clearer understanding of the change in accident risk over time. Third, the effect of urbanisation on accident severity over time is also studied in a developing country (i.e. Jordan).

Table 1 – Literature that used the ARDL approaches to investigate traffic accidents

Reference	Explanatory variables	Country (period of study)	Conclusion
[29]	Foreign direct investment, health expenditures, trade openness, mobile subscriptions, the number of researchers, and environmental particulate matter	OECD countries (1995–2015)	Road traffic fatalities showed short-run bidirectional causality with foreign direct investment and health expenditures. A reduction in road fatalities with trade openness and research for road safety.
[22]	Energy consumption, gross domestic product per capita, vehicle kilometres travelled, number of motor vehicles, divided road length, and population growth	Turkey (1970–2018)	Increase in the number of population and car ownership increases traffic accidents. An increase in the length of the divided highway reduces traffic accidents.
[21]	GDP, growth of population, expansion of road infrastructure and growth of private car ownership	Hong Kong, China (1984–2015)	Road traffic frequency showed a proportional relationship with population growth and car ownership, but an inverse relationship with the expansion of the road network.
[28]	Health force density index, temperature, rainfall, road lengths	Pakistan (1985–2016)	A Granger causality from road traffic fatalities to high type road length is detected. Also, road fatality is increased by rainfall and high-type road length but decreased by health force density.
[35]	GDP per capita, number of doctors per 10,000 populations, degree of urbanisation, unemployment rate, and motorisation rate)	Iran (1991–2011)	The main determinants of accident fatalities are: GDP per capita, doctors per 10,000 populations, degree of urbanisation and motorisation rate, with no effect on the unemployment rate.
[36]	Percent GDP, population growth and employment rate	New Zealand (2018–2025)	An integrated road safety baseline is developed to reduce traffic accident casualties. The ARDL model was identified as the preferred time-series approach.

The rest of the paper is organised as follows: Section 2 describes the applied data. The proposed nonlinear model and subsequent diagnostic tests are presented in Section 3. Sections 4 and 5 present the results and conclusions of the paper, respectively.

2. DATA DESCRIPTION

To study and compare the application of the nonlinear ARDL model a case study for accident traffic accident data was obtained from Jordan. The accident severity index in urban areas was examined with five demographic and economic independent variables. The data were collected from different resources. Traffic accident data were collected from the Jordan Traffic Institute [1] and it included the number of accidents with deaths and injuries categorised by district (i.e. urban or rural). These data were used to calculate the annual accident severity index (*Equation 1*) using Alam and Tabassum (2023) formula [37], which is the dependent variable in this study.

$$Severity\ index = 3.0 * X_1 + 1.8 * X_2 + 1.3 * X_3 + 1.0 * X_4 \quad (1)$$

where X_1 is fatal crashes, X_2 is major injury crashes, X_3 is minor injury crashes, X_4 is property damage crashes.

The accident severity variable will be shortened to (AS) hereafter. The other annual independent variables are GDP growth rate (GDP), the proportion of population living in urban areas (UP), total length of the road networks (RL), vehicle ownership growth rate (VO) and newly added building areas (BA). Data for the first three independent variables were collected from the World Bank [38], while the subsequent data were collected from the Jordanian Department of Statistics [39].

The study covers the annual period from 2004 to 2022. During these 19 years, Jordan witnessed important events that affected its traffic characteristics and demographic and economic variables. These events include but are not limited to, the Syrian and Iraqi crises and the displacement of large numbers of their residents to Jordan. This heterogeneity occurring in the study period suggests that a nonlinear framework should be used to better understand the interaction between AS and RL, UP, GDP, BA and VO variables. The aforementioned annual variables were converted into quarterly frequency using the quadratic match sum method [40,41]. The quadratic match sum method is used to transform data from low frequency into high frequency. This method helps increase the degree of freedom of the data without affecting its nature.

Descriptive statistics of all variables are presented in *Table 2*. The normality check is also included in *Table 2* and is measured by three tests: skewness, kurtosis and Jarek-Pera tests. The RL and GDP are positively skewed (or skewed to the right) while the other variables (i.e. AS, UP, BA and VO) are skewed to the left. The AS and VO present an excess of kurtosis above 3 which can be visualised as a thin 'bell' with a high peak while other variables show decreased kurtosis. The Jarque–Bera test indicates the non-normality of all the data series at the 5% significance levels, except for the AS and UP.

Table 2 – Descriptive statistics

	AS	RL	UP	GDP	BA	VO
Mean	26876	7659	87.31	3.91	6221	5.50
Median	27365	7419	89.13	2.76	6149	6.06
Maximum	30954	9307	91.90	8.81	8233	110.5
Minimum	19927	6371	77.95	-1.46	2919	-101.0
Std. Dev.	2404	724	4.35	2.75	1367	43.66
Skewness	-1.011	0.636	-0.771	0.479	-0.545	-0.106
Kurtosis	3.84	2.86	2.22	2.19	2.83	4.82
Jarque-Bera	15.21*	5.18	9.44*	4.97	3.86	10.60

*Note: * indicate variable significance at 95% confidence level.*

Figure 1 shows the dynamics of the considered variables over the study period and helps in giving a first impression of the series' stationarity.

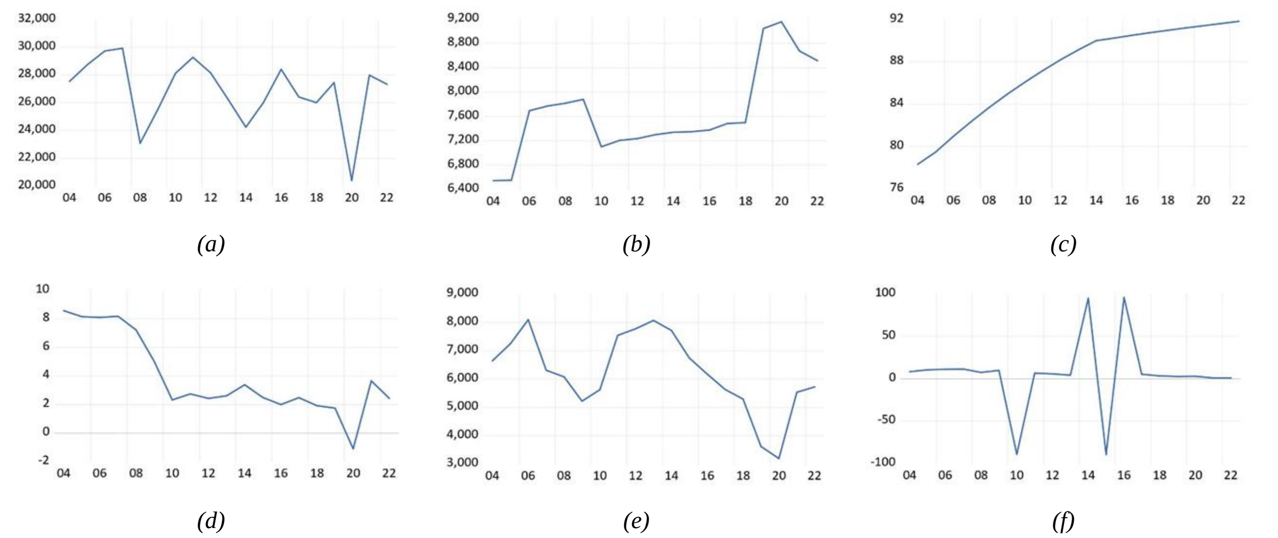

Figure 1 – The annual time series plot of (a) AS, (b) RL, (c) UP, (d) GDP, (e) BA and (f) VO over the period from 2004 to 2022

3. METHODOLOGY

Numerous studies have explored a variety of variables to explain traffic accident severities. However, there are scarce studies that mainly use the economic and demographic characteristics of a country to determine the change in accident severity over time. The prosperity of any country, urban sprawl and the expansion of building areas and road lengths may have an impact on traffic conditions in general and traffic safety in particular. Therefore, the model in this study is presented as follows:

$$AS_t = f(RL_t, UP_t, GDP_t, BA_t, OV_t) \tag{2}$$

where, f denotes the functional notation.

The Ordinary Least Squares regression (OLS) is a common technique for predicting coefficients of linear regression that describe the relationship between a dependent variable and one or more independent variables. The OLS regression estimates the coefficient by fitting a best-fit line linearly for the data. However, unlike cross-sectional data, time series data are not randomly sampled; it can look like they are related, but they are not. The OLS regression may ignore the auto-correlation between series over time. Therefore, applying OLS regression in forecasting asymmetric data can generate a spurious regression. To deal with nonlinear series, many models have been proposed, such as the ARDL and the nonlinear ARDL.

3.1 Standard ARDL model

Applying the OLS regression for a non-stationary time series on another non-stationary one may result in a spurious regression. In statistics, the spurious correlation is a mathematical relationship in which two or more variables are associated but not causally related, due to the chance or the presence of a third unobserved factor. In this case, the adjusted R-squared is not sufficient.

The autoregressive distributed lag (ARDL) model [42], uses F-statistic to test the existence of co-integration on the short-run and long-run effects of the independent variables on the dependent variable. Co-integration helps in finding a genuine relationship between non-stationary time series not through linear regression directly but through understanding the long-run relationship between the series. The deviance of co-integration between dependent and independent variables at some sticky periods can be detected by the residual error correction model (ECM) and explained in short-run dynamics. In contrast, a long-run equilibrium is captured when the variables converge again in the long-run showing negative ECM values. The ECM makes it possible to deal with non-stationary data series and separates the long- and short-run.

The ARDL model requires all series to be stationary. Non-stationary time series must be transformed into stationary by integrating the series of order k. The order of integration, denoted by I(d), of a time series is the minimum number of lad differences required to obtain a covariance stationary series. For example, stationary series are integrated of order 0 or level is denoted by I(0). If the series is non-stationary at level but is stationary at the first lag difference, then the series is integrated at order one, I(1).

The benefits of the ARDL compared to previous models can be summarised as follows.

1) This model can be applied to a small sample size data.
2) It is useful when variables are combined in either the zero I(0) or one I(1) integration order [43, 44]. In contrast, other models such as the VECM and VAR require all variables to have the same order of integration [42].
3) The model helps to derive the ECM and explain short-run deviance.
4) In the ARDL model, endogeneity is less of an issue because it is free of residual correlation [42, 45].

Apart from the ARDL advantages, one limitation of this model is that it cannot be used when any of the variables are integrated at the order 2, I(2). Therefore, the stationarity of variables must be checked in advance. The Augmented Dickey-Fuller (ADF) [46] test is usually applied to check series stationarity. The ADF test tests the null hypothesis that

H_0: There is a unit root in a time series sample

The alternative hypothesis varies depending on the version of the test used but is usually stationarity or trend-stationarity. If the series is not stationary, a one lag difference is applied and the ADF is applied again until it is stationary. ADF-GLS is an extension of the ADF developed by [47] and is more useful when the sample size is small.

Once these test statistics indicate that none of the variables are integrated in the second order, estimating the ARDL coefficients is the next step. The ARDL analysis is divided into two parts. Firstly, the long-run effect of the independent variables on the dependent variable is estimated and the co-integration is examined using the F-bounds test statistics. Secondly, the presence of a long-run co-integration between the AS and the independent variables is examined. The F-test can be used by restricting the long-run coefficients of the lagged level [42, 48], i.e.

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$$

$$H_A: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 = 0$$

Rejecting the null hypothesis confirms the co-integration relationship between variables (or the presence of a long-run relationship). Then, the ARDL is used to compute two asymptotic sets of critical values at the lower and upper bounds, I(0) and I(1), respectively. If the F-statistics value exceeds the upper bound critical value, we conclude the presence of long-run integrations regardless of the integration order. If the F-statistics value falls below the lower bound, the null hypothesis cannot be rejected for no co-integration. If the F-statistics value falls between the two bounds the result would be inconclusive.

If a co-integration is detected, the ECM is predicted in the next step. The ECM is computed using the least square technique to determine the time period during which the deviation in the dependent variable is removed and to estimate the short-run effect of independent variables on the dependent variable. The standard ARDL model is presented below, based on the variables used in this study.

$$\begin{aligned}\Delta AS_t = {} & \beta_0 + \beta_1 AS_{t-1} + \beta_2 RL_{t-1} + \beta_3 UP_{t-1} + \beta_4 GDP_{t-1} + \beta_5 BA_{t-1} + \beta_6 VO_{t-1} + \sum_{i=1}^{n1} \alpha_1 \Delta AS_{t-i} \\ & + \sum_{i=0}^{n2} \alpha_2 \Delta RL_{t-i} + \sum_{i=0}^{n3} \alpha_3 \Delta UP_{t-i} + \sum_{i=0}^{n4} \alpha_4 \Delta GDP_{t-i} + \sum_{i=0}^{n5} \alpha_5 \Delta BA_{t-i} + \sum_{i=0}^{n6} \alpha_6 \Delta VO_{t-i} \\ & + \in_t \end{aligned} \tag{3}$$

where AS_t denotes the dependent variable, and RL, UP, GDP, BA and VO denote the independent variables. Δ is the first difference operator, $n1, n2, .., n6$ are the optimal lag order for each variable selected by Akaike's Information Criterion (AIC). Moreover, β_n and α_n are the long-run and short-run coefficients, respectively. The residual error $\in_t$ is assumed to be normally distributed and white noise.

3.2 Standard nonlinear ARDL model

Estimation of an asymmetry relationship with symmetric techniques appears to be biased and may lead to an improper understanding of traffic accident characteristics. Typical OLS regression models may not capture the change (upward or downward) in the effect of explanatory variables over time. Moreover, the traditional ARDL approach always deals with a constant long-run ECM ignoring any expected fluctuations in the relationship between variables.

For this reason, the non-linear ARDL (NARDL) is recently [34] used to explain these asymmetry relationships both in the short-run and long-run. In addition to its dynamic properties, the model benefits from the original ARDL advantages. In other words, the model can be applied with a combined integration order of zero and one for a nonlinear small sample size.

The normality check of this study proves the non-linear characteristics of variables. Therefore, to explore asymmetries relationships both in the short-run and long-run, the NARDL approach is required. The nonlinear version of the ARDL is formulated by substituting the positive and negative partial sums of the series into *Equation 3*, as shown in *Equation 4*.

$$\Delta AS_t = \beta_0 + \beta_1 AS_{t-1} + \beta_2 RL_{t-1}^{+} + \beta_3 RL_{t-1}^{-} + \beta_4 UP_{t-1}^{+} + \beta_5 UP_{t-1}^{-} + \beta_6^{+} GDP_{t-1} + \beta_7^{-} GDP_{t-1} + \beta_8 BA_{t-1} + \beta_9 VO_{t-1}^{+} + \beta_{10} VO_{t-1}^{-} + \sum_{i=1}^{n1} \alpha_1 \Delta AS_{t-i} + \sum_{i=0}^{n2} (\alpha_2^{+} \Delta RL_{t-i}^{+} + \alpha_3^{-} \Delta RL_{t-i}^{-}) + \sum_{i=0}^{n3} (\alpha_4^{+} \Delta UP_{t-i}^{+} + \alpha_5^{-} \Delta UP_{t-i}^{-}) + \sum_{i=0}^{n4} (\alpha_6^{+} \Delta GDP_{t-i}^{+} + \alpha_7^{-} \Delta GDP_{t-i}^{-}) + \sum_{i=0}^{n5} \alpha_8 \Delta BA_{t-i} + \sum_{i=0}^{n6} (\alpha_9^{+} \Delta VO_{t-i}^{+} + \alpha_{10}^{-} \Delta VO_{t-i}^{-}) + \in_t \quad (4)$$

where $n1, n2, .., n$ are lag order obtained using the AIC criterion. $\beta_1, \beta_2, .., \beta_{10}$ and $\alpha_1, \alpha_2, .., \alpha_{10}$ are the long-run and short-run coefficients, respectively. Positive partial sum is indicated by the upper "+" suffix, negative partial sum is indicated by the upper "−" suffix. Moreover, β_0 and $\in_t$ are the intercepts and the residual error, respectively.

Similarly to ARDL procedures, the stationarity of the series must be checked before estimating the dynamic model parameters. Nonlinearity tests must also confirm the presence of asymmetric characteristics in the series distributions. However, this study will test the presence of significant upper and/or lower asymmetry for all nonlinear independent variables.

3.3 Granger causality and other diagnostic tests

Granger causality test

This study applied the Engle and Granger causality test [49] to examine the interconnection between variables by analysing the directional moves or causality. The Granger causality tests the short-run relationship by examining whether the information provided by lagged values of one variable allows for a more accurate prediction of the value of another variable present. The Granger causality does not mean causality but rather indicates the existence of a correlation between the past value of one variable and the present value of another variable. The null and alternative hypotheses of the test are described as follows:

H_0: Variable X does not Granger cause variable Y

H_A: Variable Y does not Granger cause variable X

In our study, X is one of the independent variables: RL, GDP, UP, BA and VO, while Y is AS. Rejecting the null hypothesis confirms the directional causality from X to Y. In contrast, the failure to reject the null hypothesis confirms the statement 'Variable X does not Granger cause variable Y.' The causality results between X and Y can be bidirectional, unidirectional or none. If it is found that variable X Granger causes variable Y, variable X could be used to predict future movement in variable Y.

Wald test

The Wald test is used to find out whether the explanatory variables in a model are significant or not. 'Significant' means they add something to the model; variables that add nothing can be removed without affecting the model fit.

The null and alternative hypotheses for any specific parameter β^* in the model are:

$$H_0: \beta^* = 0$$
$$H_A: \beta^* \neq 0$$

The zero value indicates no effect of β^* on predicting a dependent variable. Rejecting the null hypothesis indicates that the variable in the model can be deleted without affecting the model in any meaningful way.

Heteroscedasticity test

Heteroskedasticity is defined as a situation where the variance of the residuals is unequal scatter over a range of measured values. The estimated coefficients of explanatory variables are obtained to be statistically insignificant with heteroskedasticity [50]. To apply heteroskedasticity for series regression models, Breusch-Pagan-Godfrey heteroskedasticity was used.

H_0: There is no heteroscedasticity

H_A: There is heteroscedasticity

When the f-statistics provides a non-significant p-value greater than 5%, the decision rule is not to reject the null hypothesis (i.e. the null hypothesis H0: there is no heteroscedasticity there) that infers homoskedasticity of the residual.

Serial correlation test

Serial correlation implies the autocorrelation in the regression residuals. In other words, serial correlation occurs when the errors in the regression are not independent of each other.

H_0: There is no serial correlation

H_A: There is serial correlation

Similarly to the heteroskedasticity test, when the p-value is greater the 0.05, no serial correlation exists in the regression model.

Structural stability test

To check the structural stability test, recursive estimation has been applied. In this study, two stability tests were applied: the Cumulative Sum (CUSUM) and the Cumulative Sum of Squares (CUSUMQ). CUSUM and CUSUMSQ tests [51] were used to detect the structural stability of series models. The CUSUM has higher power if the break is in the intercept whereas the CUSUMSQ has higher power if the structural change includes a slope coefficient.

H_0: There is no structural change in variables

H_A: There is a structural change in variables

The decision rule is that we cannot reject the null hypothesis if the CUSUM or CUSUMQ lines lie between two critical lines at a 5% significance level. This implies that the model is structurally stable over study time.

4. RESULTS AND DISCUSSION

This study analyses and compares the application of two series models, the ARDL and NARDL, to study the effect of some demographic and economic explanatory variables in urban areas on the severity of traffic accidents.

Each data series has been checked for stationarity at zero and one difference lag using the ADF and ADF-GLS tests, as in *Table 3*. Our findings show that half of the variables are stationary at the zero level (AS, GDP, OV) while the other half are at the first difference (RL, UP, BA) with 1%, 5% and 10% significance levels. In other words, the null hypothesis is rejected for all variables at order 1 without a need for second-order difference. Thus, all series can be applied to the proposed models.

Table 3 – Stationary test results at the level and first difference

Test	AS	RL	UP	GDP	BA	OV
ADF	-4.64***	-2.03	-1.94	-2.19**	-2.13	-2.38**
ADF (-1)	-3.03***	-3.29***	-3.28*	-6.23***	-4.07***	-3.33***
ADF-GLS (0)	-4.36***	-1.10	-2.29	0.03	-2.11**	-2.48**
ADF-GLS (1)	-2.74***	-2.98*	-2.93*	-2.14**	-4.00**	-3.30***

*Note: The number represents the t-statistics values. ***, **, * indicate rejection of the null hypothesis of the existence of a unit root at the significance levels of 1%, 5% and 10%, respectively.*

To facilitate the reading, the results of applying each model to the data series are presented in different subsections below, followed by some diagnostic tests.

4.1 Results of the OLS model

Applying multiple linear regression to time series data may result in spurious regression especially when the data is not normally distributed. However, for comparison purposes, this study will begin by applying OLS regression. *Table 4* displays the OLS result for the current data series. The only two significant variables are the GDP and BA. The model has a relatively low R-squared (0.236). In general, the OLS regression fails to account for residual heteroskedasticity. Therefore, more specialised time series models are needed to deal with the current data.

Table 4 – Estimates based on the OLS model

Variable	Coefficient
RL	-0.328
UP	160.35
GDP	437.48*
BA	0.527*
OV	-8.460
C	10445
Adj. R-squared	0.236
CUSUM	Stable
CUSUMQ	Stable
Serial correlation	Sig.
Heteroscedasticity	Sig.

*Note: *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.*

4.2 Results of the ARDL model

After ensuring the stationarity of the series, Schwarz's Information Criterion (SIC) [52] is used to determine the optimal lag length for all dependent and independent variables. SIC balances model fit with model complexity to determine the most parsimonious specifications. Choosing the optimal lag is important in increasing model accuracy as it uses one or more lags of the same variable to predict the current dependent variable. Analysis of the current series resulted in (3,0,0,3,3,0) optimal lag lengths, as shown in *Table 5*. The first optimal lag number (i.e. 3) indicates that the model uses the first, second and third lagged variables of the same dependent variable (AS) to predict the current AS. Moreover, GDP and BA have also added three more lagged variables to improve the model fit.

Next, in *Table 5*, the bounds test estimates of the ARDL model confirm the existence of a dynamic long-run equilibrium relationship between the AS and the UP, GDP, UE, RL and BA for all lagged variables. This is proved by the critical f-statistic (4.63) which exceeded the upper limit of the 1% significance level.

Table 5 also depicts the estimation of ARDL coefficients and other diagnostic tests. As a reminder, the ARDL model uses two components to explain the behaviour of the dependent variable: the lag of the dependent variable itself and the current and lagged values of the independent variables. The first panel of *Table 5* shows the short-run dynamic results. The short-run coefficients indicate that both the GDP and the BA, with their lag difference values, except Δ BA(-1), have a significant impact on the AS. Moreover, the first and second difference lagged of the dependent variable (i.e. Δ AS(-1)=0.475, Δ AS(-2)=0.331, respectively) have also a positive significant impact on the current AS. More specifically, increasing the present value but reducing the lagged value of GDP has a significant positive effect on traffic accident severity (AS). In contrast, positive and negative values of the lagged and current BA, respectively, would decrease the AS.

Over the long run, only the UP and the GDP show a significant effect (i.e. p-value<0.001) on the AS. For every unit increase in the percent of population in urban areas (UP) the GDP is expected to increase the AS by 342.5 and 779.9 units, respectively. Such a result indicates that Jordan's urbanization and growth in its GDP inversely affect the traffic accident severity. This result may contradict some previous studies conducted in developed countries [13]. This can be explained by the lack of sufficient development of traffic safety measures with the increase in GDP in developing countries such as Jordan, specifically in urban areas.

Table 5 – Estimates based on the ARDL model

Variables	Coefficient
Short run coefficients	
Δ AS(-1)	0.475***
Δ AS(-2)	0.331***
Δ GDP	1678.3***
Δ GDP(-1)	-848.7***
Δ GDP(-2)	-599.7**
Δ BA	-1.149***
Δ BA(-1)	0.640
Δ BA(-2)	0.643*
Long run coefficients	
RL	-0.758
UP	342.5***
GDP	779.9***
BA	-0.028
OV	-10.11
Diagnostic tests	
Bound test	4.63***
Adjusted R-squared	0.710
ECM	-0.216***
CUSUM	Stable
CUSUMQ	Stable
Serial correlation	Not Sig.
Heteroskedasticity	Not Sig.

*Note: *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.*

The ECM coefficients are negative and highly significant, implying the ability of the short-run variables, shown in *Table 5*, to converge back in the long-term at a 21.6% speed. The adjusted R-square for the overall model is 0.71. The stability of the model is verified by the CUSUM and CUSUMSQ tests, which indicates a stable model at the 5% significant level. Moreover, no significant heteroskedasticity is detected by the error indicating a homoscedastic residual. Next, the consistency of the variables in the model is checked by the Wald test (*Table 6*). Applying the Wald test indicates that we cannot reject the null hypothesis of symmetry for the RL and the OV in the long-run.

Finally, our study depicts the results based on the Granger causality test in *Table 7*. The estimated coefficients show a significant causality from the BA to the AS but not vice versa. In other words, the past values of the BA can be used to predict the current AS. In contrast, a bidirectional causality is found between the AS and the GDP.

Table 6 – The estimated Wald test for the ARDL model

Short run				
RL	**UP**	**GDP**	**BA**	**OV**
-	-	4.152**	4.247***	-
Long run				
0.007	25.098***	7.480***	6.700**	1.681

Table 7 – Granger causality test estimate for ARDL model

Null hypothesis	F-Statistic
ΔAS → ΔBA	2.596**
ΔBA → ΔAS	0.990
ΔAS → ΔGDP	1.968*
ΔGDP → ΔAS	3.102***
ΔAS → ΔOV	1.724
ΔOV → ΔAS	0.653
ΔAS → ΔRL	1.295
ΔRL → ΔAS	0.132
ΔAS > ΔUP	0.014
ΔUP > ΔAS	0.185

*Note: *, **, *** indicate significance levels of 10%, 5% and 1%, respectively.*

4.3 Results of the NARDL model

The nonlinear ARDL model adopted in this study incorporates both the long and short-run asymmetric relationship between the AS and the RL, UP, GDP, BA and VO in Jordan simultaneously. To explore the asymmetric relationship, the explanatory variables were divided into two parts, identified by the upper "+" and "−" suffixes. The "+" and "-" suffixes represent the partial sum of upward and downward movement, respectively. For instance, "GDP^{+}" indicates a positive upward effect of the GDP on the AS, while the " GDP^{-}" has a negative effect on the AS.

Before applying the NARDL model, the stationarity of all variables has been checked by the ADF and ADF-GLS techniques. The result, presented in *Table 3*, confirms the stationarity of all variables at the level and first integration order. Moreover, reviewing *Table 2* reminds us of the nonlinearity of the variables except for the BA. Nonlinearity is a category of asymmetry. This all gives an initial instinct in favour of using the NARDL model.

Table 8 shows the empirical result obtained from the NARDL model for both long and short terms.

Table 8 – Estimates based on the Nonlinear ARDL model

Variables	Coefficient
Short run coefficients	
Δ AS(-1)	0.235***
Δ AS(-2)	0.187**
Δ BA	-1.260***
Δ GDP+	1020***
Δ GDP-	1623***
Δ RL+	1.943***
Δ RL-	-5.441***
constant	7033***

Variables	Coefficient
Long run coefficients	
BA	-0.046
RL+	-0.552**
RL-	-0.649
GDP+	13.63
GDP-	-339.4*
UP+	-136.0
UP-	-70511**
OV+	-2.957
OV-	6.946*
Diagnostic tests	
Bound test	5.94***
Adjusted R-squared	0.733
ECM	-0.232***
CUSUM	Stable
CUSUMQ	Stable
Serial correlation	Not Sig.
Heteroscedasticity	Not Sig.

*Note: *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.*

The resulting bounds test of the model (5.94, p-value<0.001) indicates the presence of a dynamic long-run equilibrium relationship. The model has also a significant negative ECM value (-0.23) which confirms that the short run is converging with the long run at a 47% speed, as shown in *Table 8*.

Table 8 presents also the two-run coefficients. Interpreting the coefficients of the NARDL model is similar somewhat to the ARDL model, except that the upward and downward effect of explanatory variables is explained separately. From the table, the significant short-run coefficients included in the model are $\Delta AS(-1), \Delta AS(-2)$, and ΔBA and the two-side asymmetry of the ΔGDP and ΔRL. Both positive and negative partial sum of GDP positively affect the AS with greater intensity on the upward side (1623 units). In contrast, the RL shows an opposite effect at the two asymmetries with AS. Whereas, the increase in the RL corresponds to an increase in the most serious traffic accidents by 1.94 units, but a reduction in the least serious accidents by 5.44 units.

Investigating the long-term coefficient is more attractive. This is because the paradoxical effect of the resulting coefficients is as follows. Only the positive partial sum side of the RL affects significantly and negatively on AS. The same cannot be said for GDP, UP and OV where no significant effects are obtained at the high values of the AS (i.e. upward partial sum), but rather at the low values of AS. The downward partial sum of the OV positively affects the AS while an inverse effect is obtained for the GDP and the UP on the AS. Moreover, diagnostic tests, shown in *Table 8*, demonstrate the stability of the model as confirmed by the CUSUM and CUSUMQ tests. Furthermore, the residual of the developed NARDL model is free of heteroscedasticity and serial correlation. Finally, the results of the Wald test (see *Table 9*) support the use of all variables considered in the short run while rejecting the BA in the long run.

Finally, our study explored the results based on the Granger causality test in *Table 10*. The causality is tested between the AS and the short-run independent variables at each asymmetry separately. The estimated coefficients show a significant causality from the AS to the BA but not vice versa. Moreover, a bidirectional causality is found between the AS and the negative partial sum of the GDP.

Table 9 – The estimated Wald test for the NARDL model

Short run				
RL	**UP**	**GDP**	**BA**	**OV**
7.64***	-	25.4***	11.5***	-
Long run				
2.79*	3.71**	3.70*	0.11	5.84**

Table 10 – Granger causality test estimate for the NARDL model

Null hypothesis	F-Statistic
ΔAS → ΔBA	2.440**
ΔBA → ΔAS	0.809
ΔAS → ΔGDP+	0.358
ΔGDP+ → ΔAS	0.813
ΔAS → ΔGDP-	4.582***
ΔGDP- → ΔAS	2.560**
ΔAS → ΔRL+	0.804
ΔRL+ → ΔAS	0.043
ΔAS → ΔRL-	0.594
ΔRL- → ΔAS	1.520
ΔAS → ΔOV+	0.147
ΔOV+ → ΔAS	0.344
ΔAS → ΔOV-	0.826
ΔOV- → ΔAS	0.566
ΔAS → ΔUP+	0.131
ΔUP+ → ΔAS	0.186

*Note: *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.*

4.4 Discussion

1) There is evidence to support the existence of a long-run directional causal relationship between the GDP and accident severity, as indicated by the significant F-statistic of 2.56. This result is consistent with [21, 24, 25].
2) The significance of urban population growth with accident severity is also proved by [21, 26, 27, 36]. However, contrary to the results presented by [21], the increase in urban population is inversely related to accident severity. This can be explained by the significant increase in traffic congestion in urban Jordan which may lead to a decrease in average speed and hence accident severity.
3) The rate of vehicle ownership also affects the accident severity in the long-run, especially in the low-severity group, as shown in the results. The significance of vehicle ownership is also confirmed by [22–24].
4) Although the expansion of the road network had no effect on the ARDL model, the non-linear ARDL model succeeded in detecting its inverse effect at the upper partial sum in urban areas in Jordan. The same negative effect was also found in this reference [21].

5. CONCLUSION

This paper adapts an innovative nonlinear autoregressive distributed lag (N-ARDL) approach and compares it with the standard ARDL and the traditional ordinary least-squared (OLS) regressions. These approaches are used to examine the long-run and dynamic relationships between the accident severity in urban Jordan areas and the following independent variables: proportion of population living in urban areas (UP), GDP growth rate (GDP), total length of road network (RL), vehicle ownership growth rate (VO) and areas of newly added buildings (BA).

The data is collected annually for the period from 2004 to 2022 and then converted into quarterly using the quadratic match sum method to increase its frequency. This technique enables the expansion of the data's degree of freedom without changing the characteristics of the data. Tests of linearity revealed the weakness of normality for most variables. This can be explained by the heterogeneous events that occurred during the past 19 years. Therefore, nonlinear frameworks are suggested to better understand the interaction between variables.

According to the conventional OLS regression, the results clearly indicate that there is only a long-run equilibrium between the variables, but no short-run dynamic. However, OLS regression fails to account for data heterogeneity. Moreover, applying the OLS regression in forecasting nonstationary and/or asymmetric time series may generate a spurious regression. Using the ARDL technique accounts for endogeneity and possible dynamics among the variables. The ARDL approach can be applied to a small sample size. Moreover, it is useful when variables are combined either at the level or the first integration order. Estimates of the ARDL suggest a significant positive impact of the GDP and the UP on accident severity in the long run. Such a result indicates that Jordan's urbanization and the growth in its GDP adversely affect traffic safety. On the other hand, the expansion of building spaces in urban districts in Jordan has played a role in reducing the severity of accidents in the short-term during the past period.

However, the estimation of an asymmetry relationship with symmetric techniques appears to be biased and may lead to an improper understanding of traffic accident characteristics. Therefore, the nonlinear ARDL model is also applied to explain possible asymmetric relationships both in the short- and long-run. In addition to its dynamic properties, the model benefits from the original ARDL advantages. The NARDL estimates show a positive impact of GDP on high and low accident severity in the short run. In contrast, GDP only affects the low accident severity in the long-run. The expansion in road length (RL) presents an opposite effect at the two asymmetries. Whereas, the increase in the RL corresponds to an increase in more serious traffic accidents, but a decrease in less serious accidents. Investigating the long-run coefficients is more attractive. This is because of the paradoxical effect of the resulting coefficients as follows. Only the positive partial sum side of RL affects the accident severity significantly and negatively. In other words, the increase in the length of constructed roads in Jordan by one unit contributes significantly to reducing the intensity of high-severity accident groups. The same cannot be said for the GDP, UP and OV where no significant effects are obtained at high values of AS (i.e. upward partial sum) but rather at the low values of accident severity. Therefore, this approach helped explain the effect of the considered independent variables on the accident severity when the severity is high and low.

Granger causality results show a strong bidirectional relationship between the accident severity and the GDP. Moreover, a unidirectional causality of the BA on accident severity is also detected. The robustness of the nonlinear and standard ARDL models has also been checked by the Wald and stability tests.

The variability of results obtained by the NARDL model for the short and long run at both asymmetries is evidence of the applicability of this technique in explaining heterogeneous data. On the other hand, the results of this study help policymakers understand the impact of some demographic and economic characteristics in Jordan on accident severity. Moreover, this study urges decision-makers to monitor the impact of expected migration, whether from the countryside or from neighbouring countries that are already suffering from crises, on traffic safety. However, future work may find and use a broader range of data for more accurate results.

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معن غادي

دراسة التأثيرات غير المتماثلة للعوامل الاقتصادية والديموغرافية على شدة حوادث المرور: أدلة من نهج ARDL غير الخطي

ملخص

تتبنى هذه الدراسة نهجًا مبتكرًا للتأخر الموزع التلقائي الانحداري غير الخطي (N-ARDL) وتقارنه بالانحدار القياسي للتأخر الموزع التلقائي والانحدارات التقليدية للأقل مربعًا (OLS). تُستخدم هذه الأساليب لفحص العلاقات الديناميكية طويلة المدى بين شدة الحوادث في مدن الأردن الحضرية والمتغيرات التفسيرية التالية: نسبة السكان الذين يعيشون في المناطق الحضرية، ومعدل نمو الناتج المحلي الإجمالي، والطول الإجمالي لشبكات الطرق، ومعدل نمو ملكية المركبات، ومساحات المباني المضافة حديثًا. تغطي دراسة الحالة الفترة من 2004 إلى 2022. أظهرت تقديرات التأخر الموزع التلقائي الانحداري غير الخطي وجود تكامل مشترك طويل المدى بين المتغيرات. علاوة على ذلك، تشير تقديرات التأخر الموزع التلقائي الانحداري غير الخطي على المدى الطويل والقصير إلى تأثير متفاوت للمتغيرات التفسيرية المدروسة على شدة الحوادث عند المجموع الجزئي الموجب والسالب. بشكل عام، يؤثر نمو الناتج المحلي الإجمالي بشكل إيجابي على شدة الحوادث في الأمد القريب. في حين أن توسع طول الطريق يقدم تأثيرًا إيجابيًا وسلبيًا على المجموع الجزئي الصاعد والهابط. وعلى النقيض من ذلك، اختلفت المتغيرات التفسيرية في تأثيرها على شدة الحوادث على جانبي عدم التماثل. إن تباين النتائج التي تم الحصول عليها بواسطة نموذج ARDL غير الخطي يساعد في اقتراح سياسات مختلفة لمستويات مختلفة من السلامة المرورية العالية والمنخفضة.

الكلمات المفتاحية

شدة الحوادث المرورية، نموذج ARDL، نموذج ARDL غير الخطي، التحضر، الأردن.