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Investigating the Nexus Between Traffic Accidents and Tourism in Jordan: Evidence From the ARDL Approach

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Abstract: Several studies have examined various variables to investigate the factors contributing to traffic accidents. This paper adapts the autoregressive distributed lag (ARDL) technique to examine the long-term and dynamic relationship between traffic accident indicators and tourism in Jordan. Three levels of accidents have been studied, including fatalities, severe injuries, and minor injuries, against the following independent variables: overnight visitors, same-day visitors, tourism income, and tourist rental cars. Monthly data has been collected, covering the period from 2012 to 2021. The ARDL estimates showed the presence of long-run cointegration between variables for all accident indicators. Furthermore, the ARDL estimates on the long and short run indicate a varying effect of the considered explanatory variables by accident type. The results indicate that increased tourism income has a positive effect on the risk of minor accidents in the short-term but a negative effect on fatalities and serious accidents in the long-term. Granger causality results show a strong unidirectional effect of overnight visitors, single-day visitors, and tourism income on traffic accident indicators. The results of this study can help policymakers understand the impact of some tourism variables on traffic accidents and vice versa.

Keywords: Traffic accident; ARDL model; time series; tourism; Jordan.

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1. Introduction

Tourism has always been considered a positive contribution to economic growth and sustainable development (Oh, 2005; UNCTAD, 2013). In analyzing tourism, most researchers have focused on the economic aspect of tourism. In Jordan, the tourism industry makes a substantial contribution to the Jordanian economy. According to the Minister of Tourism and Antiquities ('Tourism statistics', 2024) the tourism sector contributed 15.6 percent of Jordan's gross domestic product (GDP) in 2023. The Jordanian government has recently realized the crucial role that expanded tourism plays in economic development, and is eager to promote tourism internationally. However, the impact of tourism may extend to other sectors, such as traffic and safety on roads, and this can only be noticed over time. Tourism and traffic researchers have not paid much attention to the empirical assessment of the contributions of tourism to traffic and vice versa.

Traffic accidents in Jordan kill between 600 and 900 people annually, with a loss of 2-3% of the country's GDP (Ghadi et al., 2018 a). There is a fairly extensive literature focused on identifying the direct contributing factors of road accidents (Al-Masaeid et al., 2020; Eboli et al., 2020; Ghadi et al., 2020). Part of the scholarship has been directed to crash scenes and inspected all related conditions (i.e., vehicle, human, and road conditions) (BIN ISLAM et al., 2008; Ghadi, 2023). Other road safety research has investigated the special change in accident risk across geographic spaces (Ghadi et al., 2018 b, 2019 a; b). However, few studies have connected traffic accidents with tourism.

Studies by Wilks et al. (1999) and Page (2009) have contributed to raising awareness of the problems that accidents can pose to the tourism industry. A negative binomial regression has been applied by Bellos et al. (2020) to investigate the effect of tourism on road accidents in Greece. It was noted in their research that both the tourist season and tourism as a purpose of travel led to an increase in road accidents, with the highest increase observed in tourist areas. However, it is usually possible to see the impact of tourism on traffic more clearly over time, so the time series approach is best for understanding such a relationship.

The autoregressive distributed lag (ARDL) is an econometric time series technique used to determine the long-run cointegration between non-stationary time series. The ARDL is more robust than the conventional time series models and performs better for small sample sizes.

Plenty of scholars have adapted a variety of time series models to study and analyze the relationship between tourism and the economy. In Morocco, El Menyari (2021) used the autoregressive distributed lag (ARDL) to study the influence of international tourism on economic growth. Meanwhile, Sharif et al. (2020) applied an extension version of the ARDL, i.e., Quantile ARDL, to analyze the impact of CO_2 emission by transportation on tourism in Malaysia. Similar research can also be found in the works of Borhan et al. (2016) and Kumar et al. (2020). On the other hand, time series methods have also been widely applied in the field of road safety. Uğuz et al. (2022) estimated the frequency of traffic accidents during the tourist season. The authors applied a hybrid deep learning model and the seasonal autoregressive integrated moving average (SARIMA) model to predict traffic accident frequencies in Antalya. Moreover, Rosselló et al. (2011) estimated the role of tourism in determining the number of accidents in a daily context in the Balearic Islands (Spain). Their results showed that 15.8% of traffic accidents are caused by tourism. Psarras et al. (2024) examined the impact of curfews during the COVID-19 pandemic and the re-opening of borders on road traffic accidents in Greece. The results revealed a decline in road traffic collisions during the lockdown period.

However, no previous work has been found that connects tourism, economics, and traffic accidents using the ARDL model, to our knowledge. This paper uses the dynamic ARDL model proposed by Pesaran (1999) and Cho et al. (2015) and the Granger causality check to investigate the relationship between the traffic accident indicators (i.e., fatality, severe, and minor accidents) in Jordan and the following explanatory variables: number of overnight visitors, number of single-day visitors, tourism income, and tourism rental car numbers. The author believes that tourism, traffic safety, and economic growth form an interconnected cycle that we must understand.

2. Data Description

The data in this research were collected from several resources. The Jordan Traffic Institute (2024) provided information on the number of deaths, serious injuries, and minor injuries resulting from traffic accidents in Jordan. Data on tourists in Jordan were collected from the Jordan Ministry of Tourism and Antiquities ('Tourism statistics', 2024), including the number of overnight visitors (ONV), single-day visitors (SDV), and tourism income (TIN). Data on the number of tourist rental cars (TRC) were obtained from the Land Transport Regulatory Commission ('Passenger Performance Indicators', 2024). All of these data were collected monthly from 2012 to 2021.

During the past 11 years, Jordan witnessed important events that affected tourism on the one hand and the traffic situation on the other. These events include the Syrian and Iraqi crises and the displacement of large numbers of those countries' populations to Jordan, the global COVID-19 pandemic, and the traffic and tourism reform programs in Jordan. Therefore, we will study the impact of each ONV, SDV, TIN, and TRC on fatal accidents, serious injuries, and minor injuries in three models and compare them.

Table 1 presents the description of the data in terms of the central tendency and the normality check. The large range of the data and the standard deviation confirm the variability of these factors during the study period, as also presented in Fig. 1. The Jarque-Bera test indicates the non-normality for data on accidents causing death and minor injuries at the 95% confidence level. Moreover, minor injuries, ONV, TIN, and TRC present a negative skewness (left-tail).

Table 1. Descriptive statistics

	DEATH	SEVERE_INJ	MINOR_INJ	ONV	SDV	TIN	TRC
Mean	55	123	1211	291557	79455	239	10103
Maximum	102	245	1729	602014	244446	543.2	12982
Minimum	12	18	366	0	0	0	6466
Std. Dev.	15	58	224	115633	49224	95	1730
Skewness	0.294	0.094	-0.372	-0.792	0.683	-0.486	-0.472
Kurtosis	3.204	1.848	3.641	3.946	3.472	4.269	2.347
Jarque-Bera	1.93	6.81*	4.83	17.01*	10.43*	12.78*	6.59*

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

3. Methodology

There is scarce literature that mainly uses tourism characteristics to explain traffic accidents over time. However, the variability of traffic volume and non-commuter drivers should have an impact on traffic conditions in general and road safety in particular. Therefore, the impacts of ONV, SDV, TIN, and TRC on the three levels of accidents (fatality, severe injury, and minor injury) in Jordan are modeled and explained in this study. Applying the conventional ordinary least square regression in forecasting non-stationary time series may generate a spurious regression. The ARDL model helps in finding a genuine relationship between non-stationary time series, not through linear regression directly but by understanding the long- and short-run relationship between the series. The ARDL uses the F-statistic to test the existence of co-integration by simultaneously examining the short-run and long-run effects of the independent variables on the dependent variable. The deviance of cointegration 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 are convergent again at the long-term showing by the negative ECM values.

The ARDL model requires all series to be stationary. Therefore, the stationarity of variables is checked by the Augmented Dickey-Fuller (ADF) test. The ADF test, proposed by Chatfield et al. (1977), is usually applied to check series stationarity. The ADF test tests the null hypothesis (H_0: There is a unit root in a time series sample). However, non-stationary time series must be transformed into stationary by integrating the series of order k.

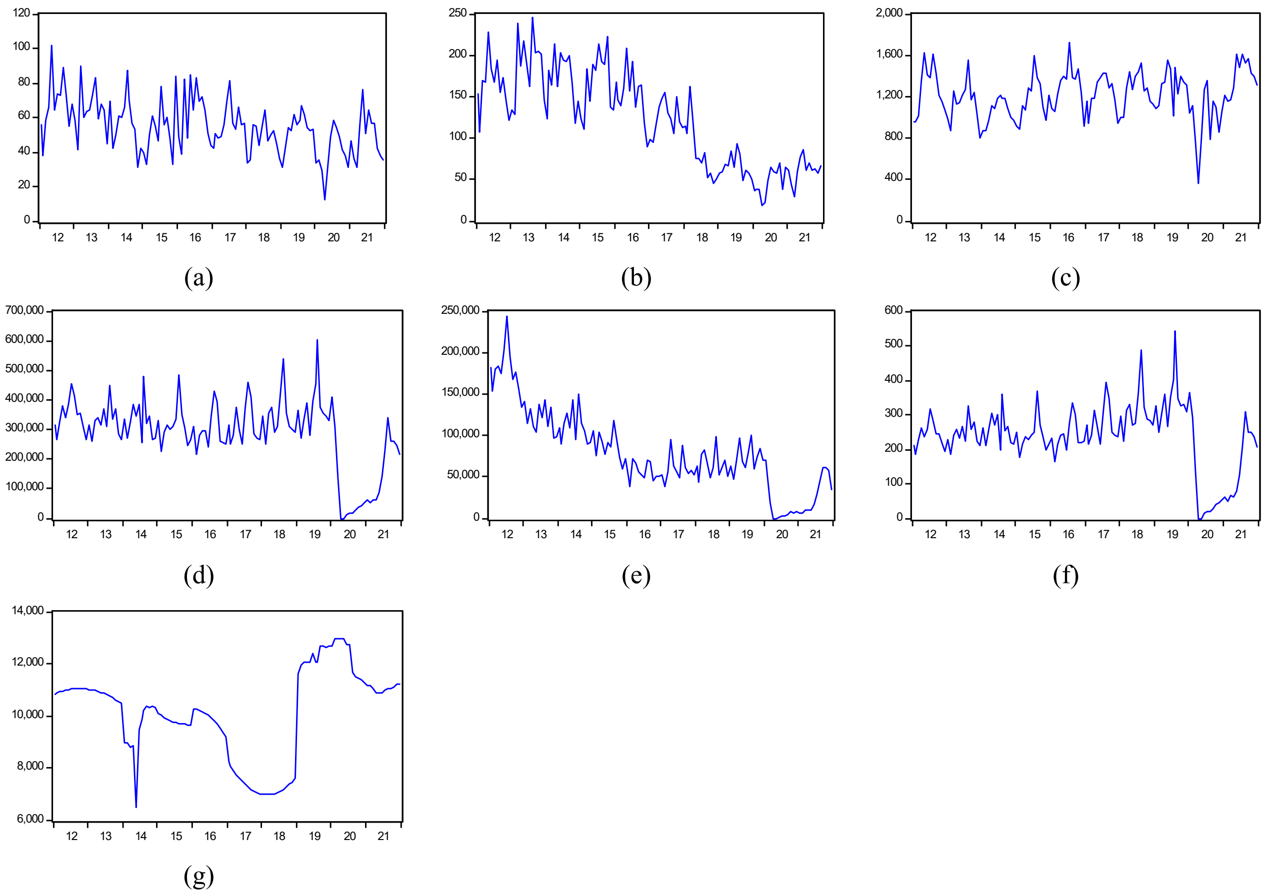

Fig. 1. The annual time series plot of (a) fatal accidents, (b) severe injuries, (c) slight injuries, (d) ONV, (e) SDV, (f) TIN, and (g) TVH over the monthly period from 2012 to 2021

The order of integration, denoted by I(d), of a time series is the minimum number of lag differences required to obtain a covariance stationary series. For example, stationary series are integrated of order 0 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). There are multiple benefits of the ARDL as compared to other time series series models. First, this model can be applied to a small sample size. Second, it is useful when variables are combined in either the zero I(0) or one I(1) integration order (Anjum, 2017; Bhutto et al., 2019). In contrast, one limitation of this model is that it cannot be used when any of the variables are integrated at the second order, I(2).

Next, ARDL model estimation can be applied. The ARDL analysis is divided into two parts. In the first part, the long-run effect of the independent variables on the dependent variable are estimated and the cointegration is examined using the F-bounds test statistics. The next step is to examine the presence of a long-run cointegration between the regressor and the independent variables. Rejecting the null hypothesis confirms the existence of a long-run relationship between variables. If a long-run cointegration is detected, the ECM is performed in the next step. The ECM is computed using the least square method to determine the short-run deviation in series.

The standard ARDL model is presented in Eq. (1), based on the variables used in this study.

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 ONV_{t-1} + \beta_3 SDV_{t-1} + \beta_4 TIN_{t-1} + \beta_5 TRC_{t-1} + \sum_{i=1}^{n1} \alpha_1 \Delta y_{t-i} + \sum_{i=0}^{n2} \alpha_2 \Delta ONV_{t-i} + \sum_{i=0}^{n3} \alpha_3 \Delta SDV_{t-i} + \sum_{i=0}^{n4} \alpha_4 \Delta TIN_{t-i} + \sum_{i=0}^{n5} \alpha_5 \Delta TRC_{t-i} + \epsilon_t \quad (1)$$

where y_t denotes the dependent variable, in our case fatal, severe, and minor accidents in three separate models. ONV, SDV, TIN, and TRC denote the independent variables. Δ is the first difference operator, and $n1, n2, .., n6$ are the optimal lag order for each variable selected by Akaike's information criterion (AIC) (Pan, 2001). Moreover, β_n and α_n are the long- and short-run coefficients, respectively. The residual error ϵ_t is assumed to be normally distributed and white noise.

Finally, the Engle and Granger causality test (Engle et al., 1987) is used to check the interconnection between variables by analyzing the directional moves or causality. 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 another variable's present value.

4. Results and Discussion

This study compares the relationship between traffic accident indicators and the tourism situation in Jordan from 2012 to 2021. Each data series has been checked for stationarity at zero and one difference lag using the ADF, as in Table 2. Our findings show that three variables are stationary at the zero level (i.e., fatal accidents, minor injuries, and SDV) while the other variables became stationary after the first lag difference with 1%, 5%, and 10% significance levels. In other words, the null hypothesis (H_0: the series has a unit root) is rejected for all variables at order $I(1)$ without a need for second-order difference. Thus, all series can be applied in the ARDL model.

Table 2. Stationary test results at the level and first difference

Test	Death Acc.	Severe inj.	Slight inj.	ONV	SDV	TIN	TRC
ADF	-6.78***	-1.80	-5.33***	-0.88	-1.70*	-0.80	-0.23
ADF (-1)	-7.94***	-17.04***	-13.27***	-2.83**	-15.86***	-2.75***	-11.73***

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.

After ensuring the stationarity of the variables, the AIC is used to determine the optimal lag length for all dependent and independent variables. The AIC balances model fit with model complexity to determine the most parsimonious specifications. Analysis of the current variables resulted in optimal lag lengths of (2,0,0,0,1), (2,0,3,0,0), and (1,2,3,1,0) for fatal, severe, and minor accident models, respectively. The first optimal lag number (i.e., 2) of the fatal accidents model indicates that the model uses the first and second lagged variables of the same dependent variable to predict the current number of fatal accidents. Moreover, ONV, SDV, TIN, and TRC also added 0, 0, 0, and 1 other lagged variables, respectively (ordered from left), to improve the model fit. The same is also applied to severe and minor injury models. Despite this, if a parameter has no lagged variable, it will not appear in the short-run table.

Next, in Table 3, the bounds test estimates of the model confirm the presence of a dynamic long-run equilibrium relationship between variables for the three models. This is shown by the critical F-statistic values which exceeded the upper limit of the 1% significance level. Table 3 also presents the estimation of ARDL coefficients. The first panel of Table 3 presents the short-run estimations. In the short run, one significant and negative lagged regressor was added to Models 1 and 3. The negative sign indicates the positive effect of the lagged regressor on safety. Furthermore, the TIN shows a significant positive effect on Model 3. In other words, as tourism income in Jordan increases, minor accidents increase by 3.66 units. The ECM values indicate that any short-run imbalance corrects toward long-run equilibrium at a speed of 62.4%, 28.5%, and 36.2% per month for Models 1, 2, and 3, respectively. In the long run, tourism income and its first lag are the only significant variables in all models. Increasing tourism income is expected to reduce death and severe accidents by 0.20 and 0.73 units, respectively. However, active tourism reflects the improvement in facilities and road safety in Jordan.

Table 3. Estimates based on the ARDL model

Variables	Coefficients		
	Death Accidents (Model1)	Severe accidents (Model2)	Slight accidents (Model3)
Short run coefficients			
ΔRegressor(-1)	-0.171*	-	-0.281***
ΔONV	-	-	-0.002
ΔONV(-1)	-	-	-0.001**
ΔTVH	-0.001	-	-
ΔSDV	-	0.000	0.000
ΔSDV(-1)	-	0.000	0.005***
ΔSDV(-2)	-	0.000	0.003***
ΔTIN	-	-	3.656*
Long run coefficients			
ONV	0.000	0.000	0.002
SDV	0.000	0.000	-0.001
TIN	-0.204**	-0.725***	-1.512
TVH(-1)	0.002***	0.002***	0.035***
Diagnostic tests			

Bound test	6.83***	4.16**	6.06***
Adjusted R-squared	0.39	0.35	0.35
ECM	-0.624***	-0.285***	-0.362***

Table 4 presents the results of the Granger causality test between the traffic accident indicators and each of ONV, SDV, TIN, and TVH. The arrows in Table 4 indicate the direction of causality. The resulting coefficients show the strength of the unidirectional relationship between ONV, TIN to fatal and minor accidents. In other words, past values of TIN and ONV can be used to predict the number of deaths and minor accidents but not vice versa. Moreover, SDV appears to be significant in predicting severe accidents.

Table 4. Granger causality test estimate for the ARDL model

	ONV	SDV	TIN	TVH
Δ Death acc. →	2.15**	1.19	1.96*	0.07
Δ Death acc. ←	0.55	0.48	0.69	0.39
Δ Severe inj. →	1.29	1.32	1.05	1.53
Δ Severe inj. ←	1.06	2.60**	0.88	0.93
Δ Slight inj. →	2.03**	1.07	1.84*	0.30
Δ Slight inj. ←	1.53	1.36	1.60	0.83

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

5. Conclusion

This paper adapts the autoregressive distributed lag (ARDL) to investigate the relationship between traffic accidents and tourism in Jordan in the long run and short run. Data were collected monthly from 2012 to 2021 and included overnight visitors, same-day visitors, tourism income, and tourist rental cars as independent variables. The impact of these variables on the number of fatalities, as well as severe and minor accidents, is investigated in three separate models.

Tests of normality revealed the weakness of linearity for most variables. This can be explained by the heterogeneous events that Jordan witnessed during recent years. Therefore, nonlinear frameworks are suggested to better understand the interaction between variables. Using the ARDL estimation technique accounts for endogeneity and possible dynamics among the variables. The ARDL approach can be applied to a small sample size of data. Estimates of the ARDL suggest a significant positive impact of tourism income on minor injury–causing accidents in the short run. However, the same variable (i.e., tourism income) appears to also be significant but negatively affects death and severe accidents in the long run. Tourism revenues account for a significant percentage of Jordan's GDP, making tourism revenue a vital contributor to infrastructure development and the enhancement of road safety measures. These improvements ultimately foster safer travel conditions for both tourists and residents in the long run. Granger causality results show a strong unidirectional effect of overnight visitors, single-day visitors, and tourism income on traffic accident indicators.

The results of this study can help policymakers understand the impact of some tourism variables on traffic accidents and vice versa. Hence, the results indicate the necessity of investing part of the tourism revenue in adopting comprehensive programs focused on green tourism, including providing an environment that encourages walking tourism, imposing rules on foreign drivers, and developing simple applications for using public transportation. However, the lack of available data was the major limitation of this study, so we hope that future work can address this issue.

Author Contributions

Maen Ghadi contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, and visualization. All authors have read and agreed with the manuscript before its submission and publication.

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