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Research paper

The impact of macroeconomic variables on the selected type of traffic crash: a study based on ARDL technique

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Abstract: Urban Jordan has witnessed substantial traffic growth in recent years. This study examines the long-term and dynamic nexus between crash rates in urban Jordan cities and macroeconomic explanatory variables. Three types of crashes have been studied including, vehicle rollover, vehicle-pedestrian crashes, and vehicle-vehicle crashes against the following explanatory variables; the proportion of the population living in urban areas, GDP growth rate, the total length of road networks, vehicle number growth rate, and spaces of the newly added building. Accordingly, a case study method has been used, covering the timeframe from 2004 to 2022, by employing the autoregressive distributed lag (ARDL) technique. The ARDL estimates showed the presence of long-run cointegration between variables for all types of crashes. Furthermore, the ARDL estimates on the long- and short-run indicate a varying effect of the considered explanatory variables by crash type. The results indicate that the expansion of the urban population and GDP growth rate play a significant role in determining crash rate in urban cities. Moreover, this study urges decision-makers to monitor the impact of expected migration on traffic safety, whether from the countryside or neighbouring countries experiencing crises.

Keywords: ARDL model, macroeconomic variables, road safety, traffic crash type, urbanization

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1. Introduction

Road traffic accidents remain a global cause of death, causing enormous economic losses and serious social consequences, especially in developing countries. In Jordan, around 70% of those that are died in road crashes are in urban cities [1]. The country suffers a loss of around 2–3% of its Gross Domestic Product (GDP) due to this issue [2, 3].

A plenty of research has concentrated on identifying the direct contributors of road crashes [4–6]. Several scholars have been focused on crash scenes to investigate all related conditions (i.e. human, vehicle, and road conditions) [7, 8]. Other traffic safety research has investigated the change in crash risk across geographic spaces [9–11]. However, these studies were often limited to short research periods, and thus overlooked the annual impact of socio-economic factors on traffic safety.

Urbanization is assumed to have a profound impact on the population in many aspects, including road safety. The anticipated migration from rural to urban areas and neighboring countries may lead to increased urban congestion, higher traffic density, and greater risks of road accidents [12]. Overloaded infrastructure and unfamiliarity with the traffic rules among migrants can exacerbate safety issues. Moreover, rapid urbanization and expansion in building spaces often outpaces infrastructure development, exacerbating risks for pedestrians [13]. To address these challenges, governments can invest in better urban planning, enforce traffic regulations, and promote public transportation. Infrastructure upgrades in rural areas can also reduce the need for migration [14]. Therefore, optimal economic, traffic and urban planning may be directly linked to improved road safety.

In the last twenty years, the major three cities in Jordan (Amman, Irbid, and Zarqa) witnessed a distinguished expansion in population frequency and construction areas. This is proved by the additional 14% of the people who have moved to live in these cities over the same period. In parallel, the large number of migrants (3.7 million) from neighbouring countries experiencing crises has also affected all aspects of life in these urban cities. On the other hand, the percentage of car ownership, in the last two decades, increased in Jordan from one car for every 58 persons to one car for every 6 persons. These economic and demographic variations have generated fluctuations in road safety in general and the type of incidents in particular. Therefore, this work concentrated on exploring the rate of change in three types of crashes (vehicle-pedestrian crashes, vehicle rolling over, and vehicle-vehicle crashes) in urban Jordan cities over the past time.

Rolling-over is one type of solo-incidents that occurs when a driver loses control of the vehicle without the involvement of others. This type of incidents constitute around 20% of all crashes. [15, 16] suggested that rollover crashes are less dangerous in urban areas because of lower driving speeds than in rural areas. Scholars explain that the main causes are the lack of use of seat belts, roadway characteristics, and the increase in the frequency of trucks on roads [17, 18]. In contrast, literature of traffic crashes in urban cities explained the patterns of pedestrian crashes with aggregated socio-economic and demographic characteristics [19] and with locations [20, 21] or both [22, 23] claimed that safety factors for pedestrians such as gender, age, type of car, and pedestrian position differ in traffic crashes in urban and suburban districts.

Vehicle-vehicle crashes are the third type of crashes result from a vehicle encountering another vehicle at any angle. This type of crash usually occurs at night when the glare of vehicle lights directly affects the driver's vision, at intersections with limited sight distance, or due to improper vehicle following rules [5, 24, 25].

Recent evidence has linked increased traffic crashes to population and motorization growth rates that has accompanied economic growth, especially in developing countries [26, 27]. In this area, a variety of time series approaches have been used to explore the key economic parameters influencing road accidents [28,29]. Autoregressive distributed lag (ARDL) is a time series model used to identify both long-run and short- run association between non-stationary time series. Long-run cointegration is usually based on historical data and is used to predict the long-term pattern between variables. The deviation in the relationship at some periods, such as the COVID-19 pandemic [30, 31], is detected through short-run dynamics. The ARDL is more robust than the traditional time series techniques and works better for small sample sizes. Many scholars have applied the ARDL model to explore the relationship between different macroeconomic parameters and road crashes [32, 33]. [34] studied the dynamic association among economic growth, motorization and traffic crashes in Nigeria. His research used the ARDL framework to address the expected endogeneity and stationarity issues in the data. The results revealed that economic growth contributes to road traffic crashes through increased vehicle use in Nigeria. [35] applied the ARDL model to examine the long-term and short-term effect of economic volatility in China on traffic crashes spanning from 1999 to 2018. The finding illuminated the positive correlation between private vehicle ownership and traffic fatalities. By adapting the same model, [36] affirmed a cointegration between traffic crashes and, GDP, registered vehicles, population frequency, road miles, as well as several driving licenses. Furthermore, [37–39] have also investigated the association between traffic crashes and socioeconomic indicators in different high and low-income countries over the short-run and long-run. A vast majority of literature have shown the significant effect of population growth and private car ownership on road incidents.

This work applied the ARDL model proposed by [40] to investigate the nexus between three types of crashes (vehicle-pedestrian crashes, vehicle rolling over, and vehicle-vehicle crashes) and macroeconomics explanatory parameters in urban Jordan cities. The five explanatory variables include proportion of the GDP growth rate, population living in urban areas, unemployment rate, total length of road networks, vehicle ownership growth rate, and areas of newly added buildings. However, the relatively small size of this data and the non-stationary series make the advantages of the ARDL approach.

Balancing economic growth and urbanization to reduce traffic accidents requires efficient urban planning and investment in safe infrastructure, such as well-designed roads and public transportation. Therefore, the contributions of this study in comparison to the previous works are as follows. First, this is the first time, to the authors' knowledge, that the ARDL model is used to study the impact of macroeconomic factors on traffic crashes. Second, the change in crash rate is compared between three types of crashes (vehicle-pedestrian crashes, vehicle rolling over, and vehicle- vehicle crashes). Third, the effect of urbanization on crash rates has also been studied over time in one developing country (i.e., Jordan).

2. Data description

This study investigates the nexus between traffic crash types and macroeconomic variables in urban Jordan cities. The used macroeconomic independent variables include the percentage of the total length of the road network (RL), number of population living in urban areas (PU), vehicle ownership growth rate (VG), GDP growth rate (GDP), and newly added building spaces (BS). The collected data are used to explain the change in urban crash rates for three types of crashes: vehicle-pedestrian collision (VTP), vehicle rollover (VRO), and vehicle-vehicle collision (VTV) in three separate models. The data were collected annually from 2004 to 2022 from different resources [1, 41, 42] and then converted into quarterly frequency with the assist of the quadratic match sum technique [43, 44]. This technique transforms data from low frequency into high frequency which helps in increasing the degree of freedom of the data without affecting its nature.

The descriptive statistics measures of all series and normality checks are presented in Table 1.

Table 1. Descriptive statistics

	VTP	**VRO**	**VTV**	**RL**	**VG**	**PU**	**GDP**	**BS**
Mean	72.24	45.84	77.94	7659	5.501	87.31	3.911	6221
Maximum	83.64	60.77	99.15	9307	110.5	91.90	8.805	8233
Minimum	66.32	21.18	65.08	6371	–101.0	77.95	–1.460	2919
Std. Dev.	3.254	9.061	9.628	724.2	43.658	4.349	2.755	1367
Skewness	1.474	–1.372	0.305	0.636	–0.106	–0.771	0.479	–0.545
Kurtosis	6.716	4.548	1.866	2.864	4.817	2.223	2.194	2.827
Jarque-Bera	71.23*	31.42*	5.251	5.184	10.596	9.441*	4.967	3.855
Note: * indicate variable significance at 95% confidence level.								

The result obtained by central tendency (i.e., mean, maximum, minimum, and standard deviation) reflect the extent of change in the given macroeconomic data and crashes distributions over the past 19 years in Jordan. During that period, Jordan witnessed significant events that affected its traffic, demographic and economic characteristics. Among these events was the Iraqi and Syrian crises and the displacement of large numbers of their inhabitants to Jordan. Furthermore, the development witnessed by urban cities did not parallel that of the countryside areas, which encouraged migration to cities. However, the fluctuation in data is also seen in normality tests. The skewness test is found to be negative for VG, VRO, PU and BS, of which VG and VRO showed excess kurtosis. The Jarque-Bera check imply the non- linearity of all the variables at the 0.95 confidence level, except for the VRO, VTP, and UP.

Figure 1 presents the dynamics of the considered variables over the study period and provides an initial indication of series stationarity.

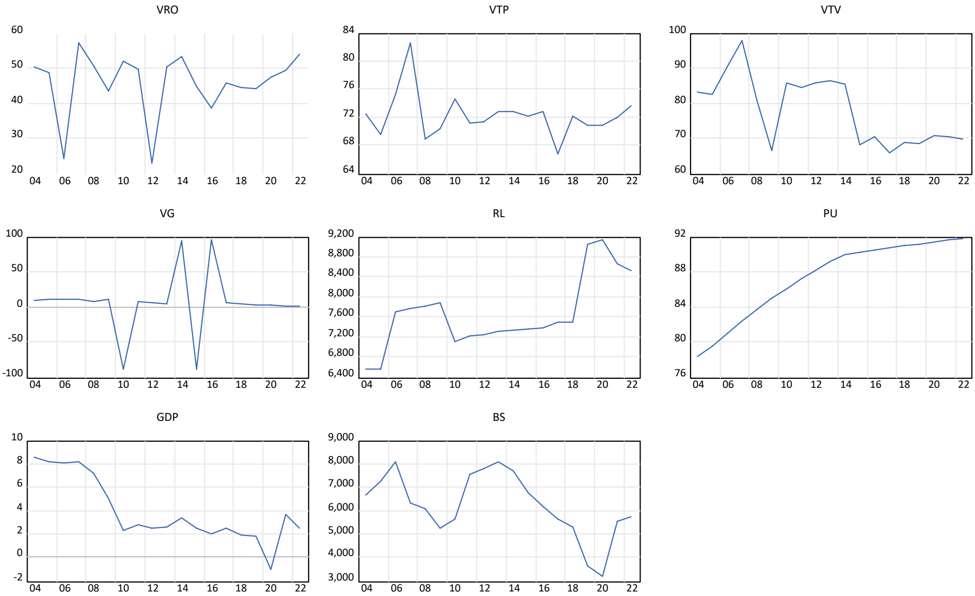

Fig. 1. The annual time series plot of VRO, VTP, VTV, RL, UP, GDP, BS, and VO over the period 2004 to 2022

3. Methodology

There is scarce literature that primarily uses macroeconomic variables to explain urban traffic crashes over time. However, urban expansion, construction of more buildings and roads, and growth of the country's GDP would affect traffic conditions in general and road safety in particular. Therefore, the effect of PU, RL, GDP, BS, and VG on the three main types of crashes (VRO, VTP, and VTV) in urban cities in Jordan are modelled and explained in this study.

The ARDL model helps in finding a genuine relationship between non- stationary time series not through linear regression directly but by understanding the long-run relationship between the series. The ARDL uses the F-statistic to test the existence of co-integration by simultaneously examining the short-term and long-term effects of the explanatory variables on the target variable. The deviance of cointegration at some periods can be identified by the residual error correction model (ECM) and explained in short-term dynamics. In contrast, a long-term equilibrium is captured when the series are convergent again at the long-term showing by the negative ECM. The ECM allows dealing with non-stationary data series and separates the long- and short-term.

The ARDL technique requires all series to be stationary. Non-stationary series have to be transformed into stationary by integrating the series of order k. The integration order, symboled by $I(d)$, of a time series is the minimum number of lag differences needed to obtain a covariance stationary series. For instance, stationary data series are integrated at order 0 denoted by $I(0)$. If the series is not stationary at the zero level but is stationary after the first lag difference, then it is integrated at order one, $I(1)$.

There are several advantages to ARDL over previous 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. 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 second order $I(2)$. Therefore, the stationarity of variables is checked by both the Augmented Dickey-Fuller (ADF) and ADF–GLS. ADF test proposed by [45] 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). Furthermore, ADF–GLS [46] is an extension of the ADF that is more useful when the sample size is small. Rejecting the null hypotheses at the first or second order of integration is required to proceed with model estimation.

Next, after checking the stationarity of all series 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 is 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. The F-test can be used by restricting the long-run coefficients of the lagged level ($H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$). Rejecting the null hypothesis confirms the existence of a long-run relationship (or cointegration relationship between variables). If the 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 below, based on the variables used in this study.

$$\begin{aligned}
\Delta y_t =\ & \beta_0 + \beta_1 y_{t-1} + \beta_2 RL_{t-1} + \beta_3 PU_{t-1} + \beta_4 GDP_{t-1} + \beta_5 BS_{t-1} + \beta_6 VG_{t-1} + \\
& \sum_{i=1}^{n1} \alpha_1 \Delta y_{t-i} + \sum_{i=0}^{n2} \alpha_2 \Delta RL_{t-i} + \sum_{i=0}^{n3} \alpha_3 \Delta PU_{t-i} + \sum_{i=0}^{n4} \alpha_4 \Delta GDP_{t-i} + \\
& \sum_{i=0}^{n5} \alpha_5 \Delta BS_{t-i} + \sum_{i=0}^{n6} \alpha_6 \Delta VG_{t-i} + \in_t
\end{aligned} \tag{3.1}$$

where y_t denotes the dependent variable, in our case is VRO, VTP, and VTV in three separate models. RL, PU, GDP, BS, and VG denote the independent variables. Δ is the first difference operator, $n_1, n_2, .., n_6$ are the optimal lag order for each variable selected by Akaike's Information Criterion (AIC). Moreover, β_n and α_n are the long- and short-run coefficients, respectively. The residual error $\in_t$ is assumed to be normally distributed and white noise.

4. Results and discussion

4.1. Unit root test

The unit root test has been used to find the stationarity of the data. Table 2 presents a stationarity check at zero $I(0)$ and first $I(1)$ integration order using both the ADF and ADF–GLS tests. The results show that the null hypothesis ($H0$: the series has a unit root) is rejected for all variables at order 1 without a need for a second-order difference. Thus, all series can be applied in the proposed model.

Table 2. Unit root test results at the level and first difference

Test	VRO	VTP	VTV	RL	PU	GDP	BS	VG
ADF	–2.85*	–2.16	–3.49**	–2.03	–1.94	–2.19**	–2.13	–2.38**
ADF(–1)	–5.39***	–8.19***	–4.87***	–3.29***	–3.28*	–6.23***	–4.07***	–3.33***
ADF–GLS (0)	–2.97***	–2.86*	–3.22**	–1.10	–2.29	0.03	–2.11**	–2.48**
ADF–GLS (1)	–3.10***	–2.55**	–2.69***	–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 10%, 5%, and 1%, respectively.								

4.2. Results of the standard ARDL model

Table 3 presents the bounds test estimates of the ARDL model confirm the existence of a dynamic long-run equilibrium relationship between variables for the three models all lagged variables. This is proved by the critical F-statistic values which exceeded the upper limit of the 1% significance level.

Table 3 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 part of Table 3 presents the short-run equilibrium results. In the short run, two lagged regressors were added to each model, while two other explanatory variables (ΔRL(–1), ΔPU(–1)) were added to the VTV model. All lagged variables have a significant positive effect on the dependent variables, except for ΔPU(–1) which shows a negative effect. Moreover, RL and BS show a significant impact with relatively low negative values on all types of crashes. In other words, expansion in building spaces and road lengths affected positively safety in urban areas in the short run. In contrast, the increase in population rate in urban cities adversely affects road safety for VTP and VTV crash types.

The ECM values indicate that any short-run imbalance corrects toward long- run equilibrium at a speed of 37.3%, 36.9%, and 22.5% per quarter for Models 1, 2, and 3, respectively. The long-run coefficients indicate that both PU and GDP significantly affect VRO and VTP with positive values ranging between 0.2–0.5. Whereas explanatory variables seem not enough to explain model 3 in the long run. Such a result indicates that Jordan's urbanization and growth in its GDP inversely affect traffic safety. This result may contradict some previous studies conducted in developed countries [27]. 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.

Diagnostic tests of Table 3 give an adjusted *R*-squared value above 50% for all models. The stability of the models is verified by CUSUM and CUSUMSQ tests which indicate stable models at the 5% significant level. Moreover, no significant heteroscedasticity or serial correlation is detected by the error indicating homoscedastic accepted models. Finally, the consistency of long-run variables in each model has been checked by the Wald test (see Table 4). Applying the Wald test indicates that we reject the null hypotheses for all variables except VG in Model 1, and VG, GDP in Model 3. In other words, the non-significant variables can be removed without affecting the overall model fit.

Table 3. Estimates based on the ARDL model

Parameters	**Model 1 (VRO)**	**Model 1 (VTP)**	**Model 1 (VTV)**
Short-run Regressors			
Regressor lags	0.435*** (ΔVRO(–1))	0.434*** (ΔVTP(–1))	0.566*** (ΔVTV(–1))
	0.308*** (ΔVRO(–2))	0.338*** (ΔVTP(–2))	0.243** (ΔVTV(–2))
ΔRL	–0.010***	–0.002**	–0.007***
ΔRL(–1)	–	-–	0.005***
ΔPU	–	5.055***	44.21***
ΔPU(–1)	–	-–	–30.37***
ΔBS	–0.004***	-–0.001***	–0.001
Long-run Regressors			
VG	-–0.0037	-–0.008**	-–0.003
RL	-–0.0002	0.001*	0.001
PU	0.247*	0.204***	0.076
GDP	0.493*	0.271**	–0.073
BS	-–0.0007	0.0003	0.001*
Diagnostic tests			
ECM	-–0.373***	–0.369	–0.225***
Bound test	5.875***	8.236***	4.486***
Adj. *R*-squared	0.574	0.603	0.698
Serial corr.	Reject *H*0	Reject *H*0	Reject *H*0
Heteroscedasticity	Reject *H*0	Reject *H*0	Reject *H*0
CUMSUM	Stable	Stable	Stable
CUMSUMQ	Stable	Stable	Stable

Table 4. The estimated Wald test for the ARDL model

	Model 1(VRO)	**Model 1(VTP)**	**Model 1(VTV)**
VG	0.129	3.43**	0.36
RL	5.507***	5.89***	8.18***
PU	3.05*	7.02***	14.66***
GDP	3.20*	6.86**	0.27
BS	2.22*	6.85***	3.95**

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

However, the variability of results in each model in both the short- and long-run emphasizes the importance of ARDL for explaining the effect of macroeconomic variables on crash types. In general, the increase in urban population appears to negatively impact safety in all types of crashes. This is confirmed by [47] who claimed that every 1% increase in urban sprawl contributes to all-mode traffic fatality by 1.49% and pedestrian fatality by 1.47% to 3.56%.

4.3. Granger causality test results

Granger causality test [48] is used to examine the interconnection between variables by analyzing the directional moves or causality. Table 5 presents the results of the Granger causality test between each regressor (first column) and each of VG, RL, PU, GDP, and BS. Arrows in the table indicate the direction of causality.

Hence, a unidirectional causality from both VG and GDP to VRO is detected by the test. In other words, the past values of VG and GDP can be used to predict the current VRO crashes. Moreover, a significant bidirectional causality is shown between VG and VTP. However, no significant causality is found between RL and all models.

Table 5. General estimates of Granger causality test

	VG	**RL**	**PU**	**GDP**	**BS**
VRO ←	8.102***	1.260	1.519	2.17*	1.702
VRO →	1.713	0.730	27.08***	0.490	0.533
VTP ←	15.73***	0.310	22.88***	0.480	0.394
VTP →	2.71**	1.177	0.154	0.366	0.322
VTV ←	1.435	0.780	0.924	1.538	3.97***
VTV →	3.84***	1.049	1.021	0.516	0.381
Note: *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.					

5. Conclusions

This study attempted to explain the dynamic relationship between crash rates in urban Jordan districts and macroeconomic explanatory variables. Three types of crashes have been studied (i.e., dependent variables) including, vehicle-pedestrian crashes (VTP), vehicle rolling over (VRO), and vehicle- vehicle crashes (VTV) against the following independent variables: GDP growth rate (GDP), proportion of population living in urban areas (PU), vehicle number growth rate (VG), total length of road networks (RL), and spaces of newly added building (BS).

In the methodology the autoregressive distributed lag (ARDL) model has been applied. Annual data has been collected covering the timeframe from 2004 to 2022 and then converted into quarterly by using the quadratic match sum method to increase its frequency. The linearity of the data is checked by Skewness, Kurtosis, and Jarque-Bera tests which revealed non-normality in most variables. The results of the ARDL approach showed the positive significance of the urban population ratio on VTP and VTV types in the short-run and VRO and VTP types (i.e. 0.25 and 0.20 units, respectively) in the long-run. More specifically, the increase in urban population rate appears to have 5 and 44 units increase of the VTP and VTV crash rates respectively but no significant impact on VRO crashes. In contrast, error correction results showed convergence towards long-run equilibrium at speeds of 37.3%, 36.9% and 22.5% per quarter for the VRO, VTP and VTV models, respectively. The presence of long-run equilibrium is also confirmed by significance bound test values (i.e. p-values less than 5%) for all models. The interpretation of the long-run coefficients highlights the significance of GDP in relation to safety. Higher GDP growth is expected to increase the risk ratios in VRO by 49% and VTP by 47%. Moreover, a unidirectional Granger causality results from both GDP and VG to VRO is revealed by the test.

Findings in both the short- and long-run for each type of model emphasizes the importance of the ARDL model in exploring heterogeneous traffic data. Therefore, the results of this work can help policymakers in understanding the effect of macroeconomic parameters in Jordan on the various types of traffic crashes. This research also urges decision makers to monitor the impact of expected migration, whether from the countryside or from neighboring countries already experiencing crises, on traffic safety. However, the results of this study showed variation in the relationship between each type of accident and the macroeconomic variables. Future work may explain each outcome in more depth and link it to some events for better understanding.

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