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Modelling the Temporal Effect of Terrorism on Tourism in Kenya

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Abstract

Terrorist attacks have escalated over the recent years in Kenya, with adverse effects on the tourism industry. This study aims to establish if a long-run equilibrium exists between terrorism and tourism in Kenya between the years 1994 and 2014. To reinforce the robustness of the results, both Autoregressive Distributed Lag (ARDL) bounds testing and the Vector Error Correction Model (VECM) techniques are used to investigate the problem. A Granger causality test is also carried out to ascertain the direction of the relationship if one exists. The evidence from ARDL and the VECM testing procedure suggest that there is no long-run equilibrium between terrorism and tourism in Kenya. Terrorism does not Granger cause tourism and vice versa. However, short-run effect indicates that terrorism negatively and significantly affects tourism.

Keywords: terrorism, tourism, causal impact, ARDL, VECM, Kenya

1. Introduction

Tourism is a leading industry in many countries in the world. It provides foreign exchange revenue and employment opportunities. Countries invest heavily in the industry to ensure they are competitive in attracting tourism demand. Promotion of international tourism is regarded as an essential part of economic development strategy by many African countries (Akinboade & Braimoh, 2010), Kenya included. Tourism is a very important sector in Kenya's economy as it is a major source of foreign exchange earnings in the economy. The sector earned about 84.6 billion Kenya Shillings (KES) comparable to 118.4 billion and 90.4 billion marketed production for the Tea and Horticulture sectors, the two leading foreign exchange earners (Kenya National Bureau of Statistics, 2016). Other benefits that the country reaps from the tourism industry include tax revenues, and employment opportunities.

However, the country currently faces terrorism threats especially from Al-Shabaab and Al Qaeda. In recent years, several terrorist attacks have occurred in Kenya causing injury, deaths of both citizens and tourists and property destruction. This has been triggered by Kenya's military intervention in Somalia in 2011. The 2015 Global Terrorism Index (GTI) report (Institute for Economics and Peace, 2015) estimates an increase in the GTI score for Kenya of about 0.362 to reach 6.66 in their zero to ten score index during the period 2013/2014. It can be argued that the purpose of these attacks are to cripple the economy by making Kenya a hostile environment that tourists cannot visit. Buigut and Amendah (2015) show that terrorism has indeed negatively affected significantly tourist arrivals and earnings in Kenya. However the literature on the impact of terrorism on tourism demand in the East Africa region is still very limited. This paper aims at making a contribution to this nascent literature by investigating the causal impact of terrorism attacks on tourism in Kenya. Methodologically we provide more robustness to our results by using two techniques; the Autoregressive Distributed Lag (ARDL) bounds testing and Vector Error Correction Model (VECM).

Terrorist activities in Kenya can be dated back to the year 1980 when the popular Norfolk hotel was bombed in the New Year's Eve. The event killed twenty and injured eighty according to National consortium for the study of Terrorism and Responses to terrorism -START, (START, 2015). The second major event was the United States of America embassy bombing on August, 7th, 1998. This was the worst ever attack in Kenya with over two hundred and twenty four casualties and over four thousand wounded. In 2002 there was a missile attack on an Israeli aeroplane taking off from the Mombasa airport. Though this was a failed attempt, Kikambala Hotel was bombed in a twin attack minutes after it had just received sixty visitors, all of whom were from Israel. Thirteen were killed and eighty injured. On 21st September 2013, Al-Shabaab gunmen attacked the Westgate shopping mall causing a siege that lasted three days. Seventy one people were killed and more than two hundred and one were injured (START, 2015).

Some studies have shown the importance of tourism to economic growth of a country. As Odhiambo (2010) states in his paper, theoretically, an increase in tourism development leads to an increase in employment. This in turn leads to an increase in economic growth. This is because tourism is considered to be a labour intensive industry. Akinboade and Braimoh (2010) find a unidirectional causality running from international tourism earnings and real Gross Domestic Product (GDP) for South Africa. According to World Travel and Tourism council WTTC (2014) the direct contribution of tourism to Kenya's GDP was KES 183.4 billion (4.8 percent of the total GDP) in 2013, and is forecast to rise to 5.2 percent per annum, from 2014-2024, to KES 314.1 billion (4.7 percent of total GDP) in 2024. The total contribution of tourism to the GDP was KES 462.8 billion (12.1 percent of GDP) in 2013, and is forecast to rise by 5.2 percent per annum to KES 791.4 billion in 2024. Given the importance of the sector to the economy, the Kenyan economy faces a major threat from terrorism. However not much work has be done to link the relationship between the two (terrorism and tourism) in the case of Kenya. Therefore if the decrease in tourism can be attributed to terrorism it is important to know in what ways and its effects. This would also shed light on what can be done to improve tourism. This study uses two techniques, VECM and ARDL, to investigate cointegrating relationship and causality between terrorism and tourism in Kenya. Though terrorism events have increased dramatically in Kenya, with significant consequences on the tourism sector, no studies have attempted to establish the temporal effects on tourism. Hence this paper is the first to establish this relationship for Kenya.

2. Literature Review

Blomberg, Fernholz, and Levin (2013) investigate the causes of transnational terrorism in a study that explores the connection between terrorism, piracy and economic prosperity. They acknowledge that terrorism is arguably the greatest security challenge facing our world today, as its effects are felt across borders and oceans because attacks are intended to spread fear far beyond the target themselves. They find that terrorism is mostly unrelated to economic conditions while piracy responds to both economic payoffs and military deterrents. Fear is one of the reasons why terrorist attacks have such a powerful social and psychological effect (White, Porter, & Mazerolle, 2013). In a study aimed at understanding patterns of terrorist activities, they use a self-exiting model for describing the temporal patterns of terrorist activities, including the observed clustering of terrorist events in time. Their findings suggest that mathematical models can be successfully applied to improve our understanding of the risk, resilience and volatility. Such models have the potential to inform policy in provision of benchmark indicators, predicting, and forecasting future risk of terrorist attack.

In a paper that uses seemingly unrelated regression model to test individual effects of domestic and transnational terrorism on tourism demand to Lebanon, Turkey and Israel, Bassil (2014), shows that the effect of terrorism on the tourism industry depends on the type of terrorism and its intensities. Moreover, he finds that significant spill over exists between Turkey, Israel and Lebanon which adds credence to the argument that terrorism does not only affect the immediate country but it may affect a whole region. Earlier research such as Drakos and Kutan (2003) have also identified spill over effects. Baker and Coulter (2007) using the UK's Department of International Development model of sustainable development find that after Bali terrorist attacks of 2002 and 2005 livelihoods were sustained with difficulty with social capital playing a significant role. The authors propose the promotion of alternative income generating opportunities as a safety net against shocks to the tourism industry.

Bac, Bugnar, and Mester (2015) explore terrorism and its impacts on the tourism industry. They stress the supposition that terrorism has been a tool of politics through-out history. They conclude that aside from improving security systems, tourism industry has to implement crisis management systems that can handle a wide range of disasters. They argue that through proper crisis management, any destination can overcome any kind of shock, whether it is a natural disaster or a terrorist attack. In a study on the influence of terrorism risk perception on purchase involvement and safety concern of international travellers, Seabra, Abrantes, and Kastenholz (2014) using sample data of 600 international tourists travelling in Portugal, Spain and Italy, find that terrorism influences the perceptions of risk that tourist associate with international travel. They state that tourists pay attention to media while seeking information for travel. Thus negative publicity on a tourist destination that suffers a terrorist attack may also suffer losses in the tourism industry. In their paper crisis management is also emphasized.

The link between tourism and development is obvious in many countries. In his paper, Feridun (2011) states that terrorism is likely to have detrimental effect on tourism in countries with persistent terror attacks. Feridun's paper aims at making a contribution to the growing literature by investigating the causal impact of terrorist attacks on the tourism industry in the case of Turkey. In mid- 1990's tourists and tourist sites emerged as a new type of terrorist target as a means of hampering the tourism sector in Turkey. He uses the ARDL approach to model the relationship between terrorism and tourism. From the test he concludes that tourism is in a long-run equilibrium level relationship with terrorism. The results further indicate the existence of a negative causal effect of terrorism on tourism.

In their paper, Buigut and Amendah (2015) study the effects of terrorism on tourism demand in Kenya using a dynamic panel approach. Their study covers the period 2010-2013 and includes a large set of countries of origin. Their results indicate that previous visits have a positive and significant effect on current arrivals. They also found that terrorism, with the number of fatalities as proxy, negatively and significantly affects the number of visitors to Kenya. Their computation shows that a 1 percent increase in fatalities decreases the arrivals by about 0.132 percent. Their computation suggests this converts to an annual loss of about 157.1 million KES in tourism revenues per unit increase in fatality for the country. The arrivals numbers they use include visitors on holidays, business and on transit. Thus in their opinion the estimated figure is likely to be an underestimate since holiday makers are likely to be more responsive to security concerns than business or transit visitors.

In another paper Buigut (2015) undertakes a comparative analysis of the effects of terrorism on the demand for tourism in Kenya between developed and emerging countries using quarterly data. He shows that arrivals from developed countries have a distinct seasonal pattern which is closely mirrored by the total arrivals, and that the seasonality depicted by the arrivals from the emerging countries is much less conspicuous. This suggests that the strong seasonality portrayed by the total arrivals is mainly driven by the pattern of arrivals from developed countries. Arrivals from developed countries show a more marked decline compared to emerging countries. In addition his estimates suggest that a 1 percent increase in fatality costs the Kenyan economy about 156 million KES per annum from the developed countries.

Fletcher and Morakabati (2008) examine the relationship between tourism activity, terrorism and political instability in the cases of Kenya and Fiji. They find no conclusive stable relationship. However they find that political events such as coups and international problems have far more effects than a low to medium, one-off terrorist attack.

In summary, quite some work has been done in relation to terrorism and tourism globally, though this literature is still very limited in Kenya. The importance of the tourism sector to an economy cannot be overlooked considering the benefits achieved. As there are many factors that would affect tourism, Lee (2011) refers to tourism as having a perishable nature. Terrorism is one of those factors that have been established to have a negative impact on tourism in many countries such as Turkey, and Kenya as well. The causal effect between tourism and terrorism is yet to be established for Kenya.

3. Methodology

3.1 Data

For this study data on tourism arrivals are acquired from the Kenya National Bureau of Statistics (KNBS). KNBS has been collecting and recording information on tourism from as early as the 1980's. With respect to terrorism data, the Global Terrorism Database (GTD) collects data from all over the world. GTD's definition of terrorism is the intentional act of violence, or threat of violence (outside of the precepts of International Humanitarian Law), by a non-state actor to attain political, economic, religious, or social goal through fear, coercion, or intimidation. The terrorism data in this database can be refined to fit one's definition of terrorism. In this study pre and post-election violence are excluded from the data and focus is put on planned bombings, shootings, kidnappings and arson attacks. Two sets of data are collected for both international tourism arrivals and terrorism fatalities: quarterly data for the period 1994Q1 to 2014Q4 and annual data from 1994 to 2014 yielding 84 and 21 observations respectively. Figure 1 shows the trend of tourist arrivals over the period 1994 to 2014.

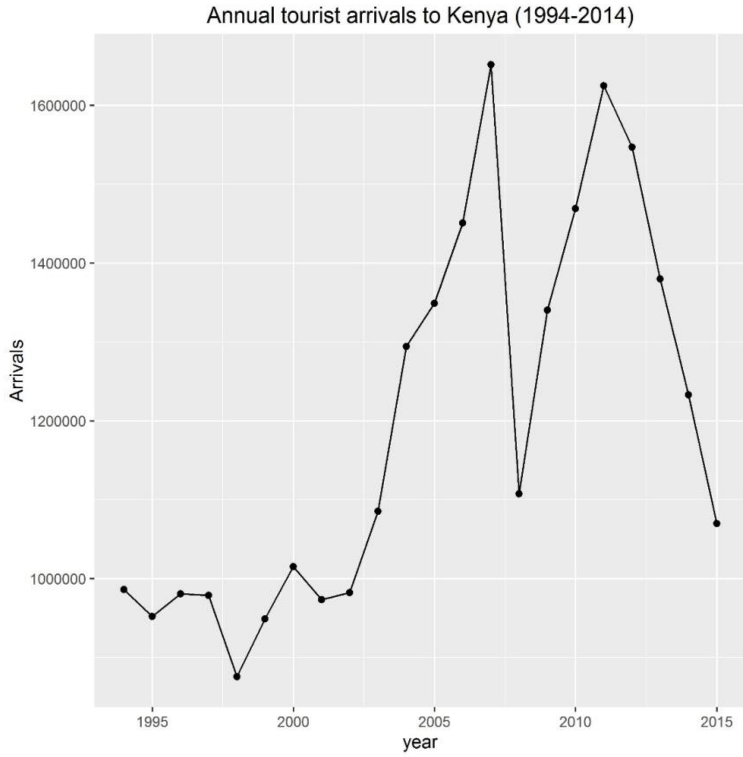

Figure 1. Annual arrivals to Kenya (1994-2014)

The two time series variables are tested for unit roots individually to determine their respective orders of integration using the Augmented Dickey Fuller (ADF) test. For the quarterly data the arrivals time series variable is found to be I(1) while the fatalities time series variable is I(0). In the annual scenario, the two time series variables are both found to be I(1). Some other exogenous variables thought to have had an impact on tourist arrivals during the period such as the world recession of 2008, a fire experienced at the Jomo Kenyatta airport in August 2013, and the election cycle are also included.

3.2 Vector Error Correction Model

The Vector Error Correction Model (VECM) offers a convenient framework for separating long-run and short-run components. So it is an improvement over the single equation Engle and Granger (1987) proposed in that it allows for more than one cointegrating relationship. The VECM can be reformulated from the VAR as follows:

$$Z_{\mathrm{t}} = A_1 Z_{t-1} + \cdots + A_k Z_{t-k} + u_t \tag{1}$$

To:

$$\Delta Z_t = \Gamma_1 \Delta Z_{t-1} + \cdots + \Gamma_{k-1} \Delta Z_{t-k+1} + \Pi Z_{t-k} + u_t \tag{2}$$

Where: $\Gamma_i = -(I - A_1 - \cdots - A_i)(i = 1, \cdots, k-1)$ and $\Pi = -(I - A_1 - \cdots - A_k)$

This way of specifying the system contains information on both the short and long-run adjustment to changes in Z_t, via the estimates of $\hat{\Gamma}_i$ and $\hat{\Pi}$. And $\Pi = \alpha\beta$ where $\boldsymbol{\alpha}$ represents the speed of adjustment to disequilibrium and β is a matrix of long-run coefficients such that the term $\beta' Z_{t-k}$ in the equation represents up to $(n-1)$ cointegration relationships in the multivariate model, which ensures that the Z_t converges with their long-run steady state solutions. (Harris & Sollis, 2005) emphasise that when Z_t is a vector of non-stationary I(1) variables, then all the terms in the equation that involve ΔZ_{t-i} are I(0) while ΠZ_{t-k} must also be stationary for $u_t \sim$ I(0) to be white noise.

Three instances are put forward (Harris & Sollis, 2005; Enders, 2010) when the requirement that $\Pi Z_{t-k} \sim$ I(0) is met.

1) When all the variables in Z_t are in fact stationary and which implies there are no problems of spurious regression and thus the appropriate modelling strategy is to estimate the standard VAR in levels.

2) When there is no cointegration at all, implying that there are no linear combinations of the Z_t that are I(0), and consequently is an $(n \times n)$ matrix of zeros. Again in this case the appropriate model is a VAR in first differences involving no long-run elements.

3) When there exists up to $(n-1)$ cointegration relationships.

The Johansen test is used to test for the cointegration rank of the two variables. It differs from the ARDL test because of its multi variable form (i.e. it tests the linear combination of the two variables for unit roots). However it requires that the variables are I(1). There are two types of the Johansen test, the eigenvalue test and the trace test. In this particular study the trace test is used. If the test concludes that there is no cointegration then a simple Vector Autoregressive (VAR) model suffices to estimate the relationship of the variables in this study. The trace statistic which is used to test for cointegration is given by:

$$\lambda_{trace} = -2\log(Q) = -T\sum_{i=r+1}^{n}\log\left(1-\hat{\lambda}_i\right) \qquad r = 0,1,2,\dots,n-2,n-1 \tag{3}$$

The VECM is tailored to our particular variables of arrivals (Arr) and fatalities (Fat). The vector $Z_t = [Arr, Fat]'$. The equation would be as follows:

$$\binom{\Delta Arr}{\Delta Fat} = \Gamma_1\binom{\Delta Arr_{t-1}}{\Delta Fat_{t-1}} + \cdots + \Gamma_{k-1}\binom{\Delta Arr_{t-k+1}}{\Delta Fat_{t-k+1}} + \Pi\binom{Arr_{t-k}}{Fat_{t-k}} + \gamma_1 elect_t + \gamma_2 rec_t + \gamma_3 fire_t \tag{4}$$

Where $elect_t$ and rec_t stand for election and recession respectively.

3.2.1 Granger Causality

The Granger Causality test is used to check for the causal direction of the time series. We test whether the fatalities influences arrivals or vice versa, or the relationship is two way (arrivals influences fatalities and fatalities influence arrivals). The test would involve testing the null hypothesis "Fat_t does not cause Arr_t" and vice versa. Running the following regression model would yield estimates that would be used to infer the Granger Causality

$$Arr_t = \lambda_0 + \sum_{i=1}^{m}\lambda_{1i}Arr_{t-i} + \sum_{i=1}^{n}\lambda_{2i}Fat_{t-i} + u_t \tag{5}$$

$$Fat_t = \phi_0 + \sum_{i=1}^{m}\phi_{1i}Fat_{t-i} + \sum_{i=1}^{n}\phi_{2i}Arr_{t-1} + \epsilon_t \tag{6}$$

Where Arr_t and Fat_t are Arrivals and Fatalities respectively. The null hypothesis that Fat_t does not Granger cause Arr_t is rejected if the λ_{2is} are jointly significant. And also the null hypothesis that Arr_t does not Granger cause Fat_t is rejected if the ϕ_{2is} are jointly significant. If both null hypotheses are rejected then this will imply that there is a dual Granger causality relationship between Arrivals and Fatalities.

3.3 ARDL

The ARDL model's advantage over the VECM is that it can be performed with variables which are integrated of different orders. In the quarterly data scenario, the time series variables arrivals and fatalities are I(1) and I(0) respectively. ARDL bounds testing approach is also more suitable and provides better results for small sample size. The ARDL format of the unrestricted ECM due to Pesaran, Shin, and Smith (2001) is as follows:

$$\Delta Y_t = a_{0Y} + \sum_{i=1}^{p}b_{iY}\Delta Y_{t-i} + \sum_{i=1}^{p}c_{iY}\Delta X_{t-i} + \sigma_{1Y}Y_{t-1} + \sigma_{2Y}X_{t-1} + \epsilon_{1t} \tag{7}$$

$$\Delta X_t = a_{0X} + \sum_{i=1}^{p}b_{iX}\Delta X_{t-i} + \sum_{i=1}^{p}c_{iX}\Delta Y_{t-i} + \omega_{1X}X_{t-1} + \omega_{2X}Y_{t-1} + \epsilon_{2t} \tag{8}$$

Δ is the difference operator, p represents the lag size, and Y_t and X_t are the underlying variables. In our case Y_t and X_t are arrivals and fatalities. In equation (7) Y_t is the dependent variable and the null hypothesis to be tested is:

$$H_{\mathbf{0}}: \sigma_{1Y} = \sigma_{2y} = 0$$

i.e. there exists no long-run equilibrium.

And the alternative hypothesis:

$$H_{\mathbf{1}}: \sigma_{1Y} \neq \sigma_{2y} \neq 0$$

With respect to equation (8) where the dependent variable is ΔX_t, the null hypothesis is:

$$H_{\mathbf{0}}: \omega_{1Y} = \omega_{2y} = 0$$

Vs the null:

$$H_1: \omega_{1Y} \neq \omega_{2Y} \neq 0$$

The hypotheses from both equations are tested using F-tests. Since exact critical values are not available for a mix of I(0) and I(1) variables Pesaran et al. (2001) provides bounds on the critical values for the asymptotic distribution of the F-statistic. If the computed F-statistic falls below the lower bound we conclude that the variables are I(0) and thus no cointegration is possible. If the F-statistic falls above the upper bound we conclude that there is cointegration. Finally if the F-statistic falls between the bounds the test is considered as inconclusive (Giles, 2013).

Long run equilibrium would mean, if the X variable changes at this moment the Y variable would be expected to change accordingly in the next time periods with some adjustment rate or vice versa. The Granger casualty test is used to ascertain the direction of the relationship if one exists. As stated earlier, our variables of interest are international tourist arrivals and terrorist fatalities. Hence, the ARDL equation with arrivals and fatalities as variables:

$$\Delta Arr_t = a_{0Arr} + \sum_{i=1}^{4} b_{iArr}\Delta Arr_{t-i} + \sum_{i=1}^{4} c_{iArr}\Delta Fat_{t-i} + \sigma_{1Arr}Arr_{t-1} + \sigma_{2Arr}Fat_{t-1} + \epsilon_{1t} \quad (9)$$

$$\Delta Fat_t = a_{0Fat} + \sum_{i=1}^{4} b_{iFat}\Delta Fat_{t-i} + \sum_{i=1}^{4} c_{iFat}\Delta Arr_{t-i} + \omega_{1Fat}Fat_{t-1} + \omega_{2Fat}Arr_{t-1} + \epsilon_{2t} \quad (10)$$

The hypothesis to be tested:

$$H_{\mathbf{0}}: \sigma_{1Arr} = \sigma_{2Arr} = 0$$

Vs

$$H_{\mathbf{1}}: \sigma_{1Arr} \neq \sigma_{2Arr} \neq 0$$

And

$$H_{\mathbf{0}}: \omega_{1Fat} = \omega_{2Fat} = 0$$

Vs the null

$$H_1: \omega_{1Fat} \neq \omega_{2Fat} \neq 0$$

4. Empirical Results

4.1 The Unit Root Tests

The augmented dickey fuller test is used to test for unit roots in the two variables arrivals and fatalities. But the test requires that you specify the lags of variables. Table 1 shows the various methods select four lags for the arrivals variable and zero lag for the fatalities variable in the quarterly scenario. While in the annual case a lag of one is preferred.

Table 1. Arrivals and fatalities lag selection for unit root tests

Quarterly						
Variable		Arrivals			Fatalities	
Lag	AIC	HQIC	SBIC	AIC	HQIC	SBIC
0	25.2083	25.2202	25.2381	9.82163*	9.83357*	9.8514*
1	24.6472	24.6711	24.7068	9.82467	9.84855	9.88422
2	24.6417	24.6775	24.731	9.82365	9.85947	9.91298
3	24.5797	24.6274	24.6988	9.82852	9.87627	9.94762
4	24.2218*	24.2815*	24.3707*	9.83697	9.89666	9.98585
Annual						
0	27.7501	27.755	27.7992	11.8432	11.8481	11.8922
1	27.1286*	27.1383*	27.2266*	11.7798*	11.7895*	11.8778*

From the results in Table 2 the null hypothesis of no unit root is rejected and it is concluded that the arrivals variable is non-stationary. Differencing the arrivals variable once and testing for unit roots using the same procedure. ADF test on first difference of the arrivals variable concludes that it is I(1) as shown from the results in Table 2.

Table 2. ADF test for unit roots on arrivals and fatalities for quarterly data

Variable	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Arrivals(levels)	-1.759	-3.539	-2.907	-2.588
Arrivals (1st differences)	-3.768	-3.541	-2.908	-2.589
Fatalities(levels)	-7.339	-3.534	-2.904	-2.587

The same procedures are implemented for the fatalities variable with zero lag yields the results in Table 2. From the results the null hypothesis of no unit roots fails rejection and hence it is concluded that the fatalities is I(0). The results from Table 3 show that both arrivals and fatalities (annual periodicity) are I(1).

Table 3. ADF test for unit roots on arrivals and fatalities annual data

Variable	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Arrivals(levels)	-1.676	-3.750	-3.000	-2.630
Fatalities(levels)	-1.546	-3.750	-3.000	-2.630
Arrivals (1st difference)	-4.968	-3.750	-3.000	-2.630
Fatalities (1st difference)	-5.445	-3.750	-3.000	-2.630

4.2 Testing for Cointegration

With respect to the study's first objective of finding if a long-run equilibrium exists, the appropriate model to be used on the quarterly set of data would be the ARDL because the variables are integrated of different orders. VECM is appropriate for the annual set of data since they are integrated of the same order (refer to Table 2 and Table 3). Exogenous variables that are thought to have influence on the tourist arrivals are incorporated into both systems. These exogenous variables are the 2008 world recession, the Jomo Kenyatta International Airport fire in 2013, and election periods. This is because the events had some effect on the arrivals during the period under study. The lag of the system of equation must also be pre-determined and Table 4 shows that the preferred lag for the ARDL equation is four and for the VECM is one.

Table 4. Lag selection for ARDL and VECM equations

		ARDL			VECM	
Lag	AIC	HQIC	SBIC	AIC	HQIC	SBIC
0	35.1021	35.1976	35.3403	39.5896	39.5994	39.6877
1	34.5492	34.6925	34.9065	38.7865*	38.8157*	39.0806*
2	34.544	34.735	35.0204	39.1718	39.2205	39.6619
3	34.5152	34.7539	35.1107	39.5172	39.5854	40.2034
4	33.9627*	34.2492*	34.6773*	39.8432	39.9309	40.7254

4.2.1 ARDL Results

Table 5 gives the critical value bounds for the F-statistic due to Pesaran et al. (2001) where k is the number of independent variables. The calculated F-statistic is 4.214. Having the null hypothesis of no cointegrating relationships, fail to reject the null when the F-statistic is less than the critical value for I(0) regressors and reject the null when the F-statistic is greater than the critical value for I(1) regressors. Since $F = 4.214 < 4.94$ rejection fails in the null at 5 percent level of significance, hence there is no cointegrating relationship between fatalities due to terrorism and tourist arrivals.

Table 5. Critical value bounds unrestricted intercept and no trend

	0.10		0.05		0.025		0.010	
K	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
1	4.04	4.78	4.94	5.73	5.77	6.68	6.84	7.84

The ARDL in its ECM format provides the short-run dynamics between fatalities and tourist arrivals. Table 6 shows the short-run relationships and it infers that lagged differences of arrivals are negatively significant in explaining differenced arrivals. This can be explained by the pattern of tourism whereby if a peak season is experienced the next periods would have less of tourist arrivals. Fatalities are not significant in explaining differenced arrivals. The exogenous variables election and recession were very significant in explaining differenced arrivals. As expected, they negatively influenced arrivals. The JKIA fire is not significant however. This mainly is explained by the fact that flights were re-routed to Moi International Airport in Mombasa, Kenya's second leading international airport. The JKIA was back to normal operations within a short while.

Table 6. Short-run relationship between fatalities and arrivals

Arrivals (1st difference)	coefficient	Standard Error	t	P-value
Arrivals Lag1 Differenced	-.730601	.1084967	-6.73	0.000
Arrivals Lag2 Differenced	-.6824818	.1029535	-6.63	0.000
Arrivals Lag3 Differenced	-.7131388	.0943747	-7.56	0.000
Fatalities Differenced	424.2178	276.1475	1.54	0.129
Fatalities Lag1 Differenced	275.9237	255.1494	1.08	0.283
Fatalities Lag2 Differenced	82.51066	215.903	0.38	0.704
Fatalities Lag3 Differenced	-76.88421	156.4129	-0.49	0.625
Election	-39542.1	14658.03	-2.70	0.009
Recession	-37620.78	15042.42	-2.50	0.015
Fire	2594.362	41053.78	0.06	0.950
Constant	17609.05	22334.53	0.79	0.433

The ARDL estimated in levels yields results in Table 7. First lag of arrivals is significant in explaining arrivals at 5 percent level of significance same as fourth lag of arrivals on current arrivals. Fatalities is significant in explaining arrivals and it negatively influences arrivals. The exogenous variables election and recession are significant in explaining arrivals with the exception of the JKIA fire.

Table 7. ARDL regression in levels with arrivals as the dependent variable

Arrivals	coefficient	Standard Error	t	P-value
Lag 1 Arrivals	.274185	.089369	3.07	0.003
Lag 2 Arrivals	.0749521	.095133	0.79	0.433
Lag 3 Arrivals	-.0375737	.0961993	-0.39	0.697
Lag 4 Arrivals	.6802391	.0913312	7.45	0.000
Fatalities	-405.4724	143.4315	-2.83	0.006
Election	-39801.41	14619.01	-2.72	0.008
Recession	-35549.15	14952.94	-2.38	0.020
Fire	-3455.547	40958.24	-0.08	0.933
Constant	17909.27	22193.93	0.81	0.422

The ARDL estimated with fatalities as the dependent variable in Table 8 suggests that a change in arrivals influences a change in fatalities. The exogenous variables do not influence change in fatalities at 5 percent level of significance.

Table 8. Short-run estimates of ARDL with fatalities as the dependent variable

Fatalities (1st difference)	Coefficient	Standard Error	P-value
Arrivals (1st difference)	-.0003106	.0001083	0.006
Lag1 Arrivals (1st difference)	-.0003422	.0001037	0.002
Lag2 Arrivals (1st difference)	-.0002433	.0001011	0.019
Lag3 Arrivals (1st difference)	-.00025	.0000975	0.013
Election	-1.025681	12.2806	0.934
Recession	-19.7345	12.28186	0.113
Fire	40.81963	32.2866	0.211

The problem of the direction of the relationship between fatalities due to terrorism and tourist arrivals is addressed using the Granger causality test. In our case a lag of four is chosen from the previous computations. We first consider if fatalities Granger cause arrivals. The computed F-statistic in this case is 1.1858 which is compared to the tabulated $F(4, 71) = 2.49$. Rejection thus fails in the null and conclude that fatalities does not Granger cause arrivals at 5 percent level of significance. Since bidirectional relationships are possible, it is prudent to test if arrivals also Granger causes fatalities, especially since Feridun (2011) observed that tourist sites became a target for terrorist in Turkey. The calculated F-static is 1.4073 which is less than the tabulated F-statistic. Hence we fail to reject the null hypothesis and conclude that arrivals does not Granger cause fatalities at 5 percent level of significance.

4.2.2 VECM Results

In the VECM model, the system is tested for cointegration using the Johansen procedure. Table 9 gives the trace statistic from the cointegration tests. In the annual data scenario, no cointegration is found to exist between fatalities due to terrorism and tourist arrivals in Kenya in the period 1994-2014.

Table 9. Trace statistic for cointegration test in VECM

Maximum rank	Eigen value	Trace statistic	5% critical value
0		9.3145*	15.41
1	0.25610	3.3975	3.76
2	0.15623		

Since the cointegration is zero as per the results in Table 9 a VAR model fits the data best. The VAR model is fitted with the exogenous variables included. The results are given in Table 10. The results imply that neither of the variables has influence on the arrivals. Since the variables are differenced in the model, the seasonality which showed past tourist arrivals has influence on current arrivals disappears. However, when the model is fitted in levels this particular trait is observable.

Table 10. VAR estimates for the annual case

	Arrivals (1st difference)			Fatalities (1st difference)		
	Coefficient	Standard Error	P-value	Coefficient	Standard Error	P-value
Lag1 Arrivals (1st diff)	-.1687546	.3721466	0.650	.0000299	.0001657	0.857
Lag1 Fatalities (1st diff)	-470.0197	491.4144	0.339	-.2995503	.2187422	0.171
Election	-120875.2	72621.63	0.096	52.5517	32.32591	0.104
Recession	81108.31	267202.2	0.761	-30.70851	118.9392	0.796
Fire	-107267.9	164467.7	0.514	76.30282	73.20917	0.297

Note. Fatalities and arrivals are both I(1).

A Granger causality test is done on the set of annual data after estimating the VAR. Like in the ARDL, we find that fatalities due to terrorism does not Granger cause tourist arrivals in Kenya and vice versa.

5. Conclusion

There is no long-run equilibrium between terrorism and tourism in Kenya in the period between 1994 and 2014 based on the ARDL bounds testing procedure and the Johansen procedure. This can be explained by the fact terrorism activities in Kenya have not been frequent in the past and it is more of a recent problem. Terrorism events spiked after 2011. However the ARDL model run in levels (i.e. the short-run estimates) suggests that fatalities due to terrorism negatively and significantly affects tourist arrivals in Kenya. Previous tourist arrivals have positive significance in influencing future tourist arrivals. This can be explained by repeat tourism whereby tourists appreciate the experience and are more likely to return in the next season. Terrorism in Kenya does not Granger cause tourism and the vice versa is also true. However, since there is some negative terrorism influence on tourism it is only prudent that the country makes well planned security measures to deter terrorism. Political stability is also of consequence in influencing tourism in the case of Kenya (Fletcher & Morakabati, 2008). A limitation of the study is that travel advisories which may also have some impact on international tourism are not taken into account. The paper has also not addressed the issue of spill over effects of terrorism in the region. This is left for future research.

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