Research Article

Open Access CrossMark

Multiple ebola virus transmission events: evidence from African countries

Abstract

In order to analyze the effects of the numbers of deaths caused by the Ebola virus volatility changes on the stability of the West African countries, we study the outbreak Ebola virus which took place in March 3, 2014 and ends in February 02, 2015. To do this, we have based our analytical approach on the analysis of the GARCH models. We used the EGARCH process to detect the asymmetric effect of volatility. To examine the international transmission of this volatility we employed the multivariate GARCH-BEKK model. The results we have found show that there is consistent evidence of volatility changes in epidemic Ebola virus period; and shocks have permanent and asymmetric effects on volatility of the west African countries. However, we can also conclude that the correlations between numbers of deaths have significantly increased during the crisis period and this confirms that the Guinean Ebola virus is transmitted between different countries which prove the contagion phenomenon. The results we have found shows that over the full sample period shocks have permanent and asymmetric effects on volatility.

Keywords: ebola virus, Africa, persistence, asymmetry, contagion, GARCH-BEKK models

Volume 7 Issue 6 - 2018

Nadhem Selmi
Department of Quantitative Methods, University of Sfax, Tunisia

Correspondence: Nadhem Selmi, Department of Quantitative Methods, Faculty of Economics, University of Sfax, Tunisia, Email nadham.selmi@yahoo.fr

Received: October 28, 2016 | **Published:** December 13, 2018

Introduction

In the recent years, numbers of deaths have undergone major fluctuations especially in times of Ebola virus or disruption. During these periods the country generally exhibit a behavior characterized by excessive volatility in numbers of deaths study. The large swings in share series observed in West African countries led the financial community to bring renewed attention to the concept of volatility. The latter is used by specialist as an indicator of risk and the change in volatility is seen as an indicator of Ebola virus and a factor of "contagion". Centers for Disease Control and Prevention[1] explain the evolution of volatility by the cyclical factors: Firstly, by the durable and pronounced decline in numbers of deaths since the peaks observed in October 2014 and repeated shocks to the financial sphere. Secondly, by rising geopolitical uncertainty and macroeconomic (geopolitical uncertainties arising from the March 2014), the questioning by specialist of the quality of medicine death in a context marked by a weakening of financial structures of companies in the wake of several cases of Ebola virus in West Africa the bases of valuation of numbers of deaths; have uncovered fraudulent accounting practices in the Guinea. Next, it can be explained by economic and statistical properties of volatility such as falling prices and increased volatility, that is to say, the asymmetry volatility highlighted by McKinley et al.,[2] & Borchert et al.,[3] & Khan et al.,[4] & Francesconi et al.,[5] and its persistence over time. In practice, both phenomena seem to explain this asymmetry in behavior: the leverage and the effect of feedback. As for structural factors, these authors examine the indirect role of collective beliefs, or the "country consensus" aggravated by mimicking the behavior of specialist which generally results in large variations in being associated with a high level of volatility. Finally, they question the techniques of managing the country risks and the development of institutional management of funds.

The excess in the volatility, increase the risk of the investments. This will encourage the investors given their aversion to risk seeking more bangs for agreeing to support this excess risk. To manage financial risks, investors find that there is very interesting to study the transmission of numbers of deaths fluctuations. Such step allows them to develop hedging strategies against the internal and external shocks. Similarly, it is very important for public authorities to understand the ways in which shocks propagate across countries in order to prepare properly for external shocks that can be transmitted to the interior. Indeed, increased integration between the various numbers of deaths worldwide has caused the transmission of virus disturbances from one country to another. This transmission has necessitated the search for a suitable explanation to the international framework and we are talking about the phenomenon of contagion.

The notion of contagion is more related to periods of Ebola virus when the phenomena of transmission of shocks are clearer given the importance of these shocks. Thus, we prefer to define contagion as the spread of disturbances from one country to another. Legrand et al.,[6] & Breman et al.,[7] & Khan et al.,[4] explained the "epidemic based contagion" by the two following development: "dynamic contagion" reflecting the development of a similar series of events in different countries and under the same set of causes common to both countries. "Spill-over contagion" that originated in different countries, because these countries have maintained for number of cases caused by the Ebola virus. Example: the Uganda in 2000 due to the highly integrated African economies. "Pure contagion" is explained by the fact that the international spread of effects (which are not effects "monsoonal" effects or "spill-over") that remain largely unexplained by current theories for which he must appeal to subjective causes (the feeling of operators, the business climate ...) or objective (the cost of information, competition from financial intermediaries). These spillovers can be incorporated in models of multiple equilibriums, and are reported in investor behavior associated with herding behavior. "Shift contagion": this form of contagion was analyzed by Forbes & Rigobon[8] who considered that contagion should be defined as an increase in economic ties between two or more economies. It is measured by the exceptional increase of the correlation of returns of financial securities, epidemic flows of the speed of propagation of a shock, the probability of a speculative attack, and finally to numbers of deaths volatility. It's actually the contagion of stress and epidemic panic. Forbes & Rigobon[9] insist to distinguish between two broad categories of approach to contagion "Crisis-contingent theories": that is to say, the contingency approach to epidemics that deal with the effect of stress on structural interdependencies and can be divided into two main branches: the models of multiple equilibrium and liquidity endogenous political economy. "No crisis-contingent theories": that is to say non-contingent approach to the Ebola virus which handles transmission of shocks through the channels of interdependence stable.

The significance of our paper is first to highlight the exceptional behavior of volatility as a trigger for Ebola virus and a contagion factor. Then provide an interpretation to the evolution of this volatility on the occasion of a new form of outbreak Ebola virus. Finally, verify the mechanisms of transmission of this volatility between African countries. We chose as a research outbreak of numbers of deaths experienced by Guinean and sent to West African countries among March 3, 2014- February 02, 2015. The choice of this virus, as part of study lies on the fact that it represents a recent case of medical distress and has affected the most dynamic economies in the Africa. This outbreak has affected economies which do not suffer from major imbalances. These findings motivate us to try to test the validity of the following hypotheses: (1) Volatility of numbers of mortalities has a temporal variation increases during the epidemic virus. (2) This excess volatility is persistent and asymmetric. (3) Mortality volatility is transmitted between different African countries, and this transmission explains the emergence of virus in this country. To start with we test the Exponential GARCH (EGARCH) model proposed by Nelson[11] for each series which will lead us to draw the necessary conclusion on the existence of the phenomena of persistence and asymmetry effect of volatility. Finally, we will focus on studying the transmission of shocks and volatility between African numbers of deaths by estimating a multivariate GARCH-BEKK. The rest of this paper is organized as follows: Section 2 deals with the econometric methodology. Section 3 presents the empirical results. Section 4 is a conclusion.

Econometric methodology

EGARCH model

We model stock market returns within an exponential GARCH (EGARCH) model suggested by Nelson.[11]

As a starting point, the return equation can be presented as:

$$r_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i} + \varepsilon_t \tag{1}$$

The EGARCH model is as follow:

$$\log\left(\sigma_t^2\right) = \omega + \beta \log\left(\sigma_{t-1}^2\right) + \alpha\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\delta}}\right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{2}$$

Where, the parameter α represents the magnitude of the conditional shock on the conditional variance. The estimate of allows one to evaluate whether shocks to the variance are persistent or not. Nelson[11] shows that γ ensures stationarity and ergodicity for the EGARCH (1,1). The parameter γ allows one to judge asymmetric volatility. If $\gamma > 1$, the positive shocks give rise to higher volatility than negative shocks, and vice versa.

GARCH-BEKK model

We employ the Bivariate BEKK GARCH model proposed by Baba et al.,[10] to start with we present each $r_t = \mu_t + \varepsilon_t$ ()

$$\mu_t | \Omega_{t-1} \rightarrow N(0, H_t) \tag{4}$$

where r_t is the daily returns vectors. ε_t represents the innovation vector for each market. Ω_{t-1} is the conditional variance-covariance matrix. Ω_{t-1} is the market information available at time $t-1$.

The estimates of matrix μ_t elements measure the own market mean spillovers and cross-country mean spillovers. This multivariate structure thus facilitates the measurement of the effects of innovations in the mean numbers of deaths of one series on its own lagged returns and those of the lagged returns of other countries.

Following Engle & Kroner,[12] the conditional covariance matrix can be written as:

$$H_t = C_0'C + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + G_{11}'H_{t-1}G_{11} \tag{5}$$

H_t can also takes the following form:

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{12}h_{12,t-1} + g_{21}^2 h_{22,t-1} \tag{6}$$

further expanded by matrix multiplication, we can write H_t as follow:

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{12}h_{12,t-1} + g_{21}^2 h_{22,t-1} \tag{7}$$

$$h_{12,t} = c_{11}c_{12} + a_{11}a_{21}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + g_{11}g_{12}h_{11,t-1} + (g_{21}g_{12} + g_{11}g_{22})h_{12,t-1} + g_{21}g_{22}h_{22,t-1} \tag{8}$$

$$h_{22,t} = c_{21}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{22}\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + g_{12}^2 h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2 h_{22,t-1} \tag{9}$$

To test for a causality effect from the first market to the second market, a_{12} and g_{12} are set to zero. The variance and covariance equations take the form:

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{12}h_{12,t-1} + g_{21}^2 h_{22,t-1} \tag{10}$$

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{22}\varepsilon_{1,t-1}^2 + a_{21}a_{22}\varepsilon_{2,t-1}^2 + g_{11}g_{22}h_{12,t-1} + g_{21}g_{22}h_{22,t-1} \tag{11}$$

$$h_{22,t} = c_{21}^2 + c_{22}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + g_{22}^2 h_{22,t-1} \tag{12}$$

Similarly, a_{21} and g_{21} are set equal to zero to test for a causality effect from the second market to the first. The maximum likelihood estimations techniques are used to estimate the Bivariate GARCH-BEKK models. The conditional log likelihood function $L(\theta)$ is as follows:

$$L(\theta)=\sum_{t=1}^{T} l_t(\theta) \tag{13}$$

where

$$l_t(\theta)=-\log 2\pi-\frac{1}{2}\log\left|H_t(\theta)\right|-\frac{1}{2}\varepsilon_t'(\theta)H_t^{-1}(\theta)\varepsilon_t(\theta) \tag{14}$$

Where θ denotes the vector of all the unknown parameters. Numerical maximization of equations (13) and (14) yields the maximum likelihood estimates with asymptotic standard errors. As robustness checks of our hypothesis that numbers of deaths exhibit high correlations during Ebola virus 2014 (contagion effect); we employ cross-country correlation technique.

Empirical results

Data and descriptive statistics

The data comprise daily total numbers of deaths calculated by "WHO" for numbers of deaths of African countries. We have chosen numbers of deaths for Guinea, Liberia and Serra Lione. The sample starts in March 3, 2014 and ends in February 02, 2015, yielding 102 observations for each series. To analyze the volatility transmission (contagion effects), Daily returns are constructed as the first difference of logarithmic prices multiplied by 100. Table 1 presents a wide range of descriptive statistics for the eight series under investigation during the four periods. As a first step, stationarity in the time series is checked by applying the Augmented Dickey Fuller (ADF) test. The results allow us to reject the null hypothesis that the returns have a unit root in favor of the alternative hypothesis (even at 5% critical value).

Table 1 Summary of descriptive statistics

	Guinea	Liberia	Sierra Lione
T	102	102	102
Mean	486.617	961.666	558.66
Std. dev.	536.97	1289.565	839.48
Skewness	1.204*	0.936*	1.839*
kurtosis	0.503	-0.789	2.790*
J.B	25.737*	17.565*	90.60*
ARCH	0.538**	0.756**	0.579**

Notes (i) J-B is the statistic of Jarque-Bera normal distribution test. (ii).)* denotes 1% significant level (iii)** denotes 5% significant level.

The Ebola virus period appears to be an extraordinary period for all studied countries, with high positive series: Guinea (486.617), (Liberia (961.666) and (558.66) for the Sierra Lione. We observe high positive numbers of deaths with high standard deviation especially in Liberia. All the numbers of deaths series are, without exception, highly leptokurtic and exhibit a strong skewness, mostly to the left indicating a high probability of occurrence of extreme points is to say the presence of rare events in the relative distributions of Guinean, Liberian and the Sierra Lione countries. This suggests the presence of asymmetry towards negative values. To check the null hypothesis of normal distribution, we calculate the Jarque-Bera test statistic and reject the null hypothesis of normality in all cases. This raises an initial problem with the asymmetry of the preferences of medical players which are naturally concerned about their risk of loss by those gains. To test for conditional heteroskedasticity, we use the ARCH test suggested by Engle (1982), which examines the null of 'no ARCH' effects. We reject the null hypothesis which suggests that the numbers of deaths indicates suffer from hetero skedasticity which prove that GARCH parameterization could be appropriate for the conditional variance processes. Examining the numbers of deaths index trends depicted graphically in Figure1, we can see that the down gliding tendency of Guinea numbers of deaths appeared clearly in March 2014 when the outbreak Ebola virus slowed. Delinquencies rose and there was a wave of bankruptcies. However, in March 2014, a new outbreak of EBOV was identified in West Africa. Cases were reported first in Guinea, then in Liberia, Sierra Leone, Nigeria and Senegal. The outbreak is the largest to date: as of 5th September 2014, 3944 cases have been reported by the World Health Organization, and 1759 deaths (World Health Organization, 2014). This plunge continued with aggravated numbers of deaths during the second half of 2014. Until after 2014, all numbers of deaths indices displayed the same down trend. This phenomenon shows that there is a contagion effect between these countries. We can observe from the comparison of the Guinean numbers of deaths index and those of the seven big countries studied that the Liberia indices increased during July 2014- February 02, 2015. Once there is a contagion relationship between countries, the capital stream of these countries flows from low return countries to high numbers of deaths ones. Figure 2 indicates the trend of each numbers of deaths returns volatility, for example large changes tend to be followed by large changes of either sign and small changes tend to be followed by small changes in all cases. There is evidence of volatility clustering; that is, periods of high volatility followed by periods of tranquility. There is also evidence of structural breaks in volatility.

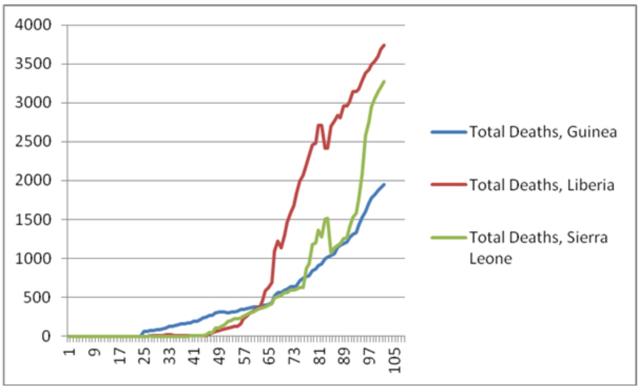

Figure 1 The numbers of deaths index trends.

The persistence and the asymmetric effect in volatility

The results reported in Table 2 show that during the Ebola virus the coefficient on β, that measures asymmetry of shocks, is negative and statistically significant at the 1 per cent level. The sign is negative, suggesting that negative shocks reduce volatility more than positive shocks. This suggests that shocks have asymmetric effects on the volatility of numbers of deaths. The sign of parameter β, permit us to captures the persistence of shocks. These parameters are positive

Citation: Selmi N. Multiple ebola virus transmission events: evidence from African countries. *MOJ Public Health.* 2018;7(6):351‒356.
DOI: 10.15406/mojph.2018.07.00267

and statistically significant at the 1 per cent level. It is very close to 1, suggesting that shocks to numbers of deaths volatility do not die out rapidly; rather, shocks tend to persist. This implies that shocks have permanent effects on numbers of deaths volatility. This finding implies that over the full period studied, positive and negative shocks have similar effects, in terms of magnitude, on stock market price volatility. We notice that the coefficient on is fairly high—close to 1—and statistically significant at the 1 per cent level, implying that shocks have persistent effects on stock market price volatility. Over the second half of 2014 to February 2015, we notice that shocks have asymmetric effects on numbers of deaths volatility, but there is evidence that shocks to volatility die out; thus, shocks are transitory. In sum, our attempt to analyze symmetry and persistence of shocks over several sub-periods reveals that there is clear evidence that shocks to numbers of deaths series volatility have asymmetric and persistent effects.

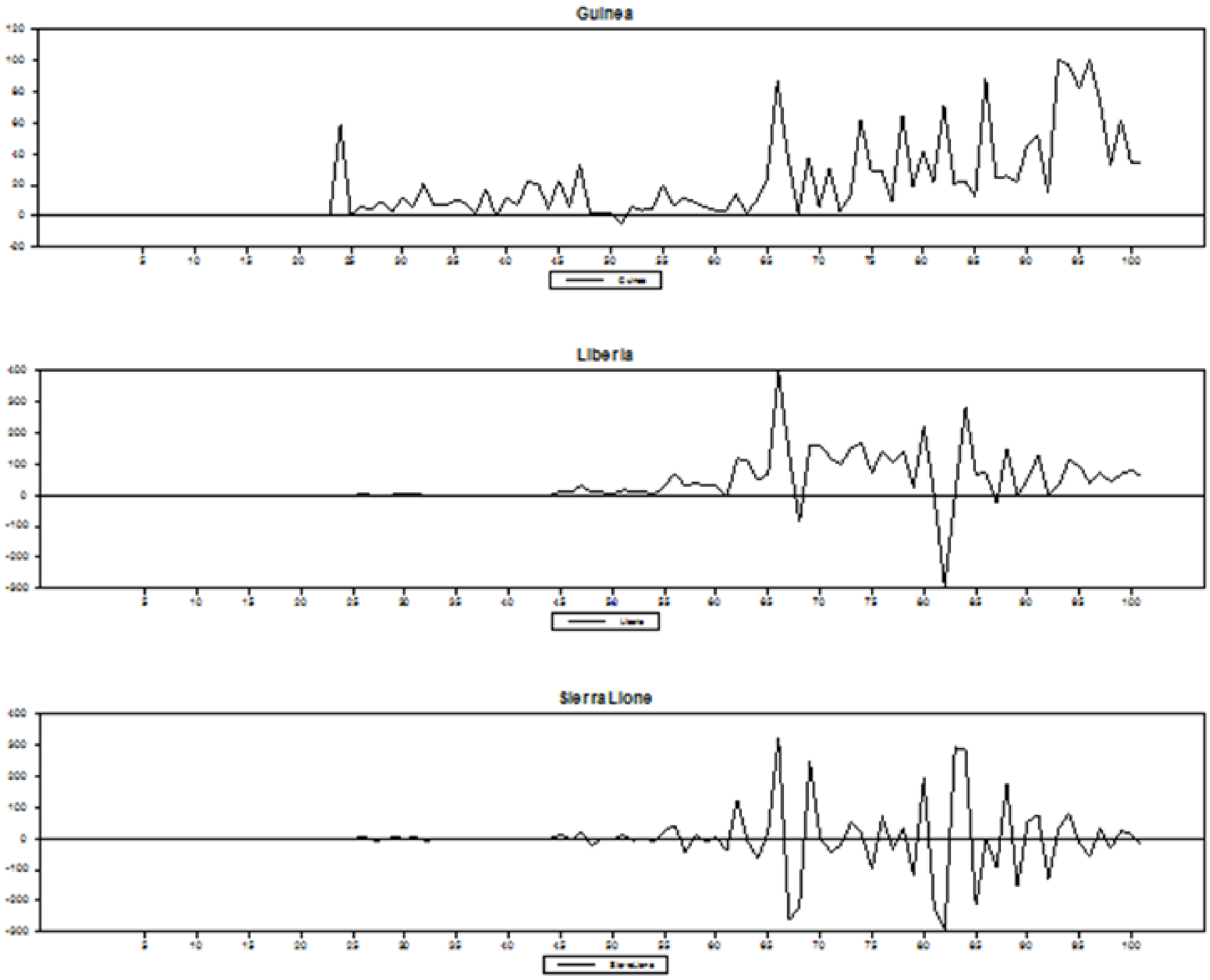

Figure 2 The numbers of deaths returns.

Table 2 Estimation results of univariate EGARCH models

	Return equations		Variance equations			
	α_0	α_1	ω	α	β	γ
Guinea	-0.12(0.22)	0.10(0.02)	0.013(0.22)	0.23(0.02)	0.54(0.00)	-0.022(0.02)
Liberia	-0.16(0.21)	0.011(0.13)	0.021(0.01)	0.018(0.01)	0.32(0.04)	-0.14(0.00)
Sierra Lione	0.02(0.03)	0.010(0.14)	-0.06(0.02)	0.06(0.03)	0.44(0.03)	-0.009(0.03)

International linkage of the west African countries

In order to examine the international linkage of numbers of deaths in West African countries four pair-wise models are estimated utilizing a bivariate GARCH framework and adopting a BEKK representation. The modeled pairs are: Guinea-Liberia and Guinea-Sierra Lione for Guinean country. For the other couples of West African we chose Liberia- Sierra Lione. Next, to see the relationship in terms of returns across the countries in each pair, we consider matrix μ_t in the mean equation (equation (3)), represented by the parameters c_{ij} in Table 3. The diagonal parameters c_{11} and c_{22} for all the modeled pairs are statistically significant, suggesting that the returns of Guinean, Liberian Union and Sierra Lione all depend on their first lags in the studied period. Then, we examine the estimated results of the time-varying variance-covariance. The matrices A and G reported in Table 3 present this relationship in terms of volatility as stated in equation (6). The diagonal elements in matrix A capture the own ARCH effect, while the diagonal elements in matrix G measure the own GARCH effect. The results reported in Table 3, show that the estimated diagonal parameters, a_{11}, a_{22} and g_{11}, g_{22} are in most cases statistically significant, indicating a strong GARCH (1, 1) process driving the conditional variances of the seven pair-wise indices. Stated a bit differently, own past shocks and volatility affect the conditional variance of indices for Guinea, Liberia and Sierra Lione. The off-diagonal elements of matrices A and G capture the cross-country effects such as shock and volatility spillovers among the seven pairs. In documenting the shock transmissions between Guinea and other countries, we find a bidirectional correlation of Guinea with West African countries; the pairs of off-diagonal parameters, a_{12} and a_{21}, are both statistically significant. This indicates a strong connection between Guinea, Liberia and Sierra Lione. Further, we find curious evidence of unidirectional linkage between Guinean and Liberia running from Liberia to Sierra Lione (i.e., only the off-diagonal parameter a_{21} is statistically significant). In other words, Liberian shocks affected mean returns in the Guinean numbers of deaths. No mean effects were found between Guinea and Liberia during the period studied. Second, we explain the volatility spillovers between Liberia and Sierra Lione of the West Africa. We identify unidirectional volatility linkages between Guinea and other countries studied as off-diagonal elements g_{11} are statistically significant for all countries except the Sierra Lione one. As concerning g_{21} are statistically insignificant in all cases except Sierra Lione. These results provide convincing evidence of the Guinean market's integration with the rest of the West Africa, particularly the sample set used in this study. However, the degree of integration is rather weak as the magnitude of estimated coefficients is quite low. Arguably, Guinea is more strongly linked with rest of the world in terms of volatility.

Table 3 Mean and volatility spillovers estimated from a bivariate GARCH (1,1)- BEKK model

	Guinea-Liberia		**Guinea-Sierra Lione**		**Liberia- Sierra Lione**	
	Coef	Signi	Coef	Signi	Coef	Signi
A	0	0.78	10.005	0	0.0009	0
B	0	0.77	-0.015	0.98	0.0009	0
C11	14.66	0	5.347	0.01	1.794	0
C21	0	0.91	0.823	0.494	1.7941	0
C22	0	0.47	0	0.99	-0.0001	0.85
A11	1.169	0	0.582	0	-1.306	0
A12	0.507	0	0.271	0.08	-0.201	0
A21	0.92	0	-0.135	0.07	0.731	0
A22	4.331	0	1.251	0	0.731	0
G11	-0.159	0	0.299	0	0.847	0
G12	0	0.98	-0.669	0	0.847	0
G21	0.01	0.52	0.404	0	-0.297	0
G22	0.078	0	0.386	0	-0.297	0
Log Lik	-604.69		-929.19		-547.43	

Notes : The diagonal elements in matrix ***C*** represent the mean equation. While matrix ***A*** captures own and cross-market ARCH effects. The diagonal elements in matrix ***G*** measure own and cross-market GARCH effects.

Citation: Selmi N. Multiple ebola virus transmission events: evidence from African countries. *MOJ Public Health.* 2018;7(6):351–356. DOI: 10.15406/mojph.2018.07.00267

Conclusion

The goal of this paper was to examine numbers of deaths volatility and its contagion on the occasion of outbreak Ebola virus. To model volatility, we used the EGARCH model, with the aim of examining whether shocks have asymmetric and persistent effects on numbers of deaths volatility. To model the volatility transmission we employ cross-country correlation techniques which support our hypothesis that numbers of deaths exhibit high correlations during epidemic Ebola virus (contagion effect). To do this, we used a bivariate GARCH-BEKK model proposed by Engle & Kroner;[12] we estimated three pair-wise models (Guinea-Liberia, Guinea-Sierra Lione and Liberia - Sierra Lione) based on daily total return indices. The results we have found shows that over the full sample period shocks have permanent and asymmetric effects on volatility. It is clear from the plot of numbers of deaths that series have not been stable; there is evidence of high volatility. This implies that shocks, whether political or economical in nature, will lead to a gradual rise or decline in numbers of deaths series depending on whether shocks are positive or negative. Then, we have analyzed the contagion effect of Ebola virus according to studied period. While there was evidence of direct linkage between Guinean numbers of death with the other markets, both in regards to returns and volatility, the linkage was strong, indicating that the Guinean numbers of deaths was totally integrated into the West African countries. Volatility spillovers were found in all cases, although the dynamics of the conditional volatilities differed. The Guinea and Liberia exhibited bidirectional linkages, while the Guinea, Liberia and Sierra-Lione display unidirectional linkages in the pre-crisis sample. The Ebola virus period showed a bidirectional connection with the Guinea and Liberia, and unidirectional ties with Sierra-Lione. Surprisingly, no statistically insignificant relations were found between the numbers of deaths of the West African countries in the Ebola virus period. Finally, highly significant, but negative, shocks and volatility spillovers were observed from Guinean to the other countries during the outbreak Ebola virus clear evidence of contagion epidemic.

Acknowledgments

None.

Conflicts of interest

Author declares that there is no conflict of interest.

References

1. Centers for Disease Control and Prevention. *Outbreaks Chronol-ogy: Ebola Hemorrhagic Fever*. 2014.
2. McKinley T, Cook AR, Deardon R. Inference in epidemic models without likelihoods. *Int J Biostat*. 2009;5:24.
3. Borchert M, Mutyaba I, Van Kerkhove MD, et al. Ebola hae-morrhagic fever outbreak in Masindi District, Uganda: outbreak description andlessons learned. *BMC Infect Dis*. 2011;11:357.
4. Khan AS1, Tshioko FK, Heymann DL, et al. The reemergence ofEbola hemorrhagic fever, Democratic Republic of the Congo 1995. *J Infect Dis*. 199;179:S76–S86.
5. Francesconi P, Yoti Z, Declich S, et al. Ebola hemorrhagic fever transmissionand risk factors of contacts, Uganda. *Emerg Infect Dis*. 2003;9:1430.
6. Legrand J, Grais RF, Boelle PY, et al. Under-standing the dynamics of Ebola epidemics. *Epidemiol Infect*. 2007;135:610–621.
7. Breman J, Piot P, Johnson K, et al. The epidemiology of Ebolahemorrhagic fever in Zaire 1976. In: Pattyn SR, editor. *Ebola Virus Haemorrhagic Fever*. Amsterdam, Netherlands; Elsevier:1978:85–97.
8. Forbes K, Rigobon R. Measuring contagion: conceptual and empirical issue. 2000.
9. Forbes K, Rigobon R. No contagion, only interdependence: measuring stock market co-movement. *NBER*. 1999:7267.
10. Baba Y Engle, Kraft RF, Kroner KF. Multivariate Simultaneous Generalized Arch. 1989.
11. Nelson D. Conditional heteroskedasticity in asset returns: a new approach. *Econometrica*. 1991;59:347–370.
12. Engle ER. Autoregressive conditional heteroscedasticity with estimates of variances of United Kingdom inflation. *Econometrica*. 1982;30(4):987–1007.