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Research Article

Contagion Effect of the Ebola Virus: Evidence of DCC and Copula Multivariate GARCH Models

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Abstract

Objective: This paper investigates contagion epidemic in a multivariate time-varying asymmetric framework, focusing on three African countries, namely Guinea, Sierra Lione and Liberia, during the epidemic Ebola virus.

Methods: Specifically, both a multivariate Gaussian copula model and the dynamic conditional correlation (DCC) approach are used to capture non-linear correlation dynamics during the period March 3, 2014- February 02, 2015. The empirical evidence confirms a contagion effect from the epidemic country to all others, for each of the examined Ebola virus.

Results: The results also suggest that Guinea is more prone to epidemic contagion, while the numbers of deaths turmoil has a larger impact than country-specific epidemic Ebola virus.

Conclusion: Our findings imply that policy responses to an epidemic Ebola are unlikely to prevent the spread among countries, making fewer domestic risks internationally diversifiable when it is most desirable.

Keywords: Ebola Virus 2014; Africa; Contagion; DCC Model

Introduction

The notion of contagion is more related to periods of epidemic when the phenomena of transmission of shocks are clearly felt. In this study, we have adopted the definition proposed by Forbes and Rigobon [1] according to them, contagion epidemic is 'a significant increase in cross-country linkages after a shock to one country (or group of countries)'.

Our focus is strictly limited to the Ebola virus 2014-2015. We apply the semi-parametric local Whittle method Künsch [2] and Taqqu and Teverovsky [3] to estimate the long memory dependencies in the volatility process of the daily frequency data through various sampling frequencies.

Understanding dependence between extremely large returns is an important research topic in death of economics. Most of past research has tended to focus only on the dependence during "normal" period conditions. There is even less research that focuses on the co-movements between numbers of deaths under extreme country conditions (such as series stress or series crash). The scant volume of literature on the extreme co-movements may be due to the lack of an appropriate tools or methodology to address the issue. In this paper, we try to fill this gap by applying a copula approach to study the relationship between numbers of deaths during the recent period.

As the DCC multivariate GARCH model is the best one to analyze contagion, we adopt a new class of this model the (DCC) [Engle [4]] and capable of estimating large time-varying covariance matrices.

It is of paramount importance in this paper to shed some light on three main issues. First, we look at the persistence of the shocks for all the countries studied (Guinea, Sierra-Lione and Liberia). Second, we identify the existence of two regimes of volatility, and show that all number of deaths series are simultaneously in the same regime. Third we examine the international transmission of the Guinea outbreak Ebola virus to the West African countries.

The rest of this paper is organized as follows: Section 2 describes the DCC multivariate GARCH models used to study the contagion effect on the total cases and total deaths. Section 3 is a discussion of the empirical results and Section 4 is a conclusion.

Materials and Methods

GARCH models

The Autoregressive Conditional Heteroscedasticity (ARCH) process proposed by Engle [5] and the generalized ARCH (GARCH) by Bollerslev and Wright [6] are well known in the volatility modeling of number of cases and number of deaths. In examining the volatility transmission between countries, however, a multivariate GARCH approach is preferred over univariate settings.

Results

Descriptive statistics	Guinea		Liberia		Sierra Lione	
	T cases	T deaths	T cases	T deaths	T cases	T deaths
T	102	102	102	102	102	102
Mean	770.80	486.617	2 100.676	961.666	1966	558.66
Std. dev.	867.178	536.97	2 973.55	1 289.565	3 039.49	839.48
Skewness	1.128*	1.204*	1.113*	0.936*	1.618*	1.839*
Kurtosis	0.086	0.503	-0.372	-0.789	1.450*	2.790*
J.B	21.697*	25.737*	21.663*	17.565*	53.45*	90.60*
ARCH	0.648**	0.538**	0.825**	0.756**	0.689**	0.579**

Table 1: The descriptive statistics of the total cases and total deaths.

(i) J-B is the statistic of Jarque-Bera normal distribution test. (ii) LB(10) is the 10-day lag return of Ljung-Box statistic, $LB^2(10)$ is the 10-day lag square return of Ljung-Box statistic. (iii)* denotes 5% significant level.

In the total cases, the number of cases mean is important in Liberia (2100.676) than the Guinea and Sierra Lione. In Liberia, also the number of deaths in mean is important than the others countries studied. Meanwhile, the standard deviation shows that the total deaths in Guinea has the highest risk (Std. dev = 536.97). The total cases in Sierra Lione takes the high risk (Std. dev = 3 039.49). The reason for higher risk could be that this period appears to be an extraordinary period for all indices studied. The skewness coefficients present the asymmetric and left-skewed distribution of Guinea, Liberia and Sierra Lione total cases and deaths. The excess 3 kurtosis coefficients exhibit a leptokurtic distribution of the Sierra Lione total cases and deaths.

Jarque-Bera (J-B) normal distribution test shows that all numbers of deaths are not normal distribution. We test further for the autocorrelation of cases and deaths through the use of Ljung-Box statistic. This also means that the heteroscedasticity of total cases and deaths should change according to time. This result suggests the use of the estimation and variance of the autoregressive conditional heteroscedasticity (ARCH) model of Engle [5].

Effects of the 2014-2015 African Ebola virus

We now consider the contagion effects of the 2014-2015 African and the volatility transmission from the Guinean to the rest of the West Africa during the outbreaks Ebola virus. For this purpose, we split our data into two subsets: total cases and total deaths. Again we examine the estimated results of the DCC multivariate GARCH for three countries; we conduct cross-country correlation analysis to find the evidence of contagion between courtiers for total cases and total deaths. Finally, using the DCC bivariate GARCH framework, we estimate three pair-wise models as explained above.

We examine the whole period to assess the repercussions of the outbreaks Ebola virus. We pay special attention to the transmission

	Guinea-Liberia-Sierra Lione
α_c	0.17* (0.01)
β_c	0.658* (0.03)
$\alpha_c + \beta_c$	0.828

Table 2: DCC multivariate GARCH models (total cases)

Notes: The value between (.) is p-value. * denotes the significant level of 5%.

of shocks and volatility. Our estimated model for the whole period shows that the linkage between the Guinean numbers of cases, the Liberian and Sierra Lione ones has increased. When standardized residuals are not auto-correlated, the maximum likelihood method can be used to obtain the mean reverting dynamic conditional correlations. Table reports the results.

We find β_c being bigger than α_c, under restriction that coefficients and $\alpha_c + \beta_c < 1$. The evidence from these results suggests that the big shock has led to the small correction in the oncoming mutual fluctuation (or covariance) between markets. The DCC model for each country shows significant coefficients for covariance matrix of u_t.

Our findings indicate that the correlation coefficients, α_c and β_c respectively are pretty small, and all are below 0.5, indicating that the selected conditioning variables contain sufficiently orthogonal information. We find β_c 0.658 being greater than α_c, 0.17 under restriction that coefficients and $\alpha_c + \beta_c < 1$ is 0.828. The evidence from these results suggests that a big shock just causes a small correction in the oncoming mutual fluctuation (or covariance) between the countries Guinea, Liberia and Sierra Lione. The results of DCC multivariate GARCH model reported show that the coefficients are significant, indicating that the dynamics of epidemics transmission from are found in African countries.

Concerning the DCC bivariate GARCH models we proved that the β_c in Guinea-Liberia (0.75) is being greater than β_c in Guinea-Sierra Lione (0.52) and Liberia-Sierra Lione (0.42). Concerning the α_c it is low for all three cases, indicating the persistence of epidemics among Liberia and Sierra Lione being greater than others countries considered.

Discussion and Conclusion

Finally, using a DCC bivariate GARCH model, we have estimated two pair-wise models. During the outbreak Ebola virus, the Liberia and Sierra Lione countries were affected by a strong contagion coming directly from the Guinea number of deaths. For the Sierra Lione country, the shocks did not come directly from the Liberia. This indicates that the Guinea country was partially integrated into the West African countries. Finally, our main results are globally robust to countries as well as the choice of alternative GARCH-type specifications allowing for both asymmetry and long memory in the conditional volatility processes, but are sensitive to the use of raw number of deaths. Consistent with previous studies focusing on number of deaths co-movement, we notice an increase in extreme dependence for several oil-exchange rate market pairs in times of epidemics [7-24].

Conflict of Interest Statement

We declare that we have no conflict of interest.

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