JOURNAL OF DEVELOPMENT ECONOMICS AND FINANCE
Vol. 5, No. 1, 2024, pp. 169-186

URL : www.arfjournals.com
https://DOI:10.47509/JDEF.2024.v05i01.08

Dependency or Interdependency Effect of the Corona-virus: Evidence of ADCC and Copula Multivariate GARCH Models

Selmi
Tunisia, Department of Quantitative Methods Faculty of Economics and Management of Sfax – Tunisia. E-mail: nadhem.selmi@yahoo.fr

Article History

Received : 12 April 2024

Revised : 15 May 2024

Accepted : 25 May 2024

Published : 27 June 2024

To cite this article

Selmi (2024). Dependency or Interdependency Effect of the Corona-virus: Evidence of ADCC and Copula Multivariate GARCH Models. *Journal of Development Economics and Finance,* Vol. 5, No. 1, pp. 169-196. https://DOI:10.47509/JDEF.2023.v05i01.08

Abstract: Objective: This paper investigates contagion epidemic in a multivariate time-varying asymmetric framework, focusing on three European countries, namely United Kingdom, France and Italy, during the epidemic corona-virus. Methods: Specifically, both a multivariate Gaussian copula model and the Asymmetric dynamic conditional correlation (ADCC) approach are used to capture non-linear correlation dynamics during the period January 22, 2020-April 30, 2020. The empirical evidence confirms a contagion effect from the epidemic country to all others, for each of the examined corona virus. Results: The results also suggest that Italy is more prone to epidemic contagion, while the numbers of deaths turmoil has a larger impact than country-specific epidemic corona virus. Conclusion: Our findings imply that policy responses to an epidemic corona virus are unlikely to prevent the spread among countries, making fewer domestic risks internationally diversifiable when it is most desirable.

Keywords: Corona virus, dependency, contagion, Asymmetric Dynamic Conditional Correlation

Background

The last decade witnessed a series of number of cases caused by outbreak-viruses affecting several countries (covid19 in China, 2020, Ebola in Africa outbreak-virus 2014, MERS-CoV, in Middle East 2012 and SARS in Asia 2002). The 2002-2004 SARS outbreaks is an epidemic of severe acute respiratory syndrome, an emerging disease caused by the corona-virus SARS-CoV, which started in November 2002 in Foshan, China. More than 8,000 people are infected and at least 774 people have died worldwide. It is considered extinct since May 2004 [WHO, 2020]. Recognized as fairly contagious (R0 ≈ 2-3, against 12-18 for measles [25]), and highly lethal (9% against 63% for Ebola), the SARS-CoV virus spreads from November 2002. Party from China, it quickly travels the globe following the axes of international passenger transport and reaches countries in a few months. The evolution of contaminations is exponential until May 2003, and then stabilizes before falling. A new form of corona-virus emerged in Saudi Arabia in September 2012. In February 2013, the first "family" outbreak was confirmed in the United Kingdom, in Manchester, in a patient who had recently traveled to the Middle East and Pakistan, was the 10th case worldwide [26]. The man's son then contracted the virus, which provided the first solid evidence of human-to-human transmission [27].

The father died on February 19, 2013. In 2013, the first two highly pathogenic cases were detected, both in Nord-Pas-de-Calais: May 7 in a 65-year-old man returning from a trip to Saudi Arabia (in the east of the kingdom) then, on May 12, 2013, in a patient who shared the hospital room of the first (end of April 2013), before his infection was known, which justified the establishment of an investigation and epidemiological surveillance system with the French Institute for Public Health Surveillance and its regional unit, the Pasteur Institute and the ARS Nord-Pas-de-Calais, under the aegis of the Ministry of Health and the General Directorate of Health. On July 4, 2013, we learned from an AFP spokesperson that the state of health of the second patient (hospitalized in Lille in France) remains critical but very stationary. The same day, we learn of a new death in Great Britain. In May 2014, the WHO estimated that MERS-CoV is transmitted by postillions and touch (much like ordinary influenza). This virus infects the person within two days of direct contact with the infected person. Contagion occurs quickly. The virus seems less deadly than what WHO thought in 2013. This disease would be estimated lethal in 38% of cases in May 2014. This virus comes directly from camels and it is transmitted to humans through the eyes and nose. Human-to-human transmission is certain.

People at high risk of serious illness from the virus should avoid close contact with animals when traveling to farms or farms located in areas where it was known that the virus could be circulating. The virus that causes COVID-19 is spread mainly by droplets produced when an infected person coughs, sneezes, or expires. These droplets are too heavy to stay in the air and fall quickly to the ground or any nearby surface. Corona-virus can be pathogenic in mammals (humans, dogs, cats

...) and birds. They include a large number of viruses causing different more or less serious diseases such as:

- Respiratory infections like the common cold. The pathology develops after an incubation period of the order of three days. After rhinoviruses, corona-viruses are the second agents of colds. These infections are seasonal, with peaks in spring and winter.
- SARS (severe acute respiratory syndrome). SARS is caused by SARS-CoV, identified in 2003. This virus is at the origin of an epidemic which started in China at the end of 2002 and which caused approximately 800 deaths.
- Middle East respiratory syndrome is caused by the MERS-CoV corona-virus. MERS-CoV was identified in 2012. The epidemic remains confined to the Arabian Peninsula, according to the Ministry of Health in June 2015.
- Covid-19 (Corona-virus Disease-19), a respiratory disease caused by an emerging corona-virus, SARS-CoV-2. The epidemic started in the city of Wuhan, China in late December 2019 and has spread rapidly around the world.

In the midst of corona virus turbulence, financial analysts and country participants worried that spillovers into other countries in Asia might increase volatility in the number of deaths series. These European countries are now suffering from the worst outbreaks corona virus since the January 22, 2020. It began with the Italy corona virus in the spring of 2020 though we think it took its real origin in late 2002 and continued with the failure of major economies in the Asia (number of deaths and cases in China, Korea and Japan) and other countries (Belgium, Russia, Tunisia, Spain), then the number of March 2020 on these countries and the spread of the numbers of deaths in their countries. In fact, these outbreaks spilled over and became the catalyst for a much broader corona-virus. The rapidity and extent of transmission of the corona virus has urged lots of experts to seek an explanation [1-3]. Some of these experts have referred to studies about previous outbreak corona virus. Important papers on prior to contagion of corona virus include [4-12] and many others.

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 [13] 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 corona virus 2019-2020. We apply the semi-parametric local Whittle method [14-16] 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 A DCC multivariate GARCH model is the best one to analyze contagion, we adopt a new class of this model the (ADCC) [17] 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 (Italy, France and U.K). 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 Italy outbreak corona virus to the European countries.

It is thus obvious from the above discussions that Italy, France and United Kingdom total cases economies have not seen the total cases decreases in the same manner and that number of cases has reasons to worry about the fluctuations in the numbers of deaths. In this context, modeling the co-movements between total cases and the total deaths are crucial, not only for country trading and risk management issues, but also for the proper regulation of total cases in all economies which operate with floating total deaths.

The rest of this paper is organized as follows: Section 2 describes the Local Whittle method, the copula approach and the ADCC 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.

2. Materiel and Methods

2.1. Local Whittle method

The classes of semi-parametric frequency domain estimators follow the local Whittle approach as suggested by [19] and analyzed by [28] (dubbing it Gaussian semi-parametric estimator). The analysis applied process is the following:

$$y_t = \mu + \sum_{j=0}^{t-1} \varphi_{j,d} x_{t-j}, t = 1 \ldots T \tag{2.1}$$

As for the Local Whittle estimator, it defined as the maximization of the local Whittle likelihood purpose, such as:

$$Q(g,d) = \log\left\{\frac{1}{m}\sum_{j=1}^{m} \lambda_j^{2d} I_y\left(\lambda_j\right)\right\} - \frac{2d}{m}\sum_{j=1}^{m}\left[\log\left(\lambda_j\right)\right] \tag{2.2}$$

Where: m $m(T)$ denotes a bandwidth number tending to infinity $T \rightarrow \infty$ except at a slower speed than T; $I(\lambda) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} e^{it\lambda}\right|^2$, represents the periodogram of X_t, and $g_x\left(\lambda\right)$ the spectral density of X_t, $\lambda_j = \frac{2\pi j}{n}$, and $j = 1,\ldots,n$.

A notable disadvantage as compared to log-periodogram estimation is that a statistical optimization is highly. Still, this estimator underlying assumptions are weaker than those pertaining to the log-periodogram regression (LPR) estimator.

In this regard, [28] have show that while $d \in \left(-\frac{1}{2},\frac{1}{2}\right)$;

$$\sqrt{m}\left(\hat{d}_{LW} - d\right) \xrightarrow{d} N\left(0,1/4\right) \tag{2.3}$$

Hence, the asymptotic distribution turns about to be extremely simple, which facilitates easy asymptotic inference. More particularly, this estimator is discovered to be more efficient than the LPR one. The reliability and asymptotic normality ranges concerning the Local Whittle estimator have explicitly been demonstrated by [30] and [29] to equate those associated the LPR estimator.

This exact LW procedure as frequency labelled, implies replacing $\lambda_j^{2d} I\left(\lambda_j\right)$ in (2.1) by $I_{\Delta^{d_y}}\left(\lambda_j\right)$, and is only valid if μ = 0 in (2.2). Since the relevant means are different from zero, [29] suggests demeaning $\{y_t\}$ with an appropriate estimator $\hat{\mu}$, and computing the exact LW estimator starting from the demeaned data. So the objective function to be minimized turns out to be:

$$R_E(m,d) = \log\left\{\frac{1}{m}\sum_{j=1}^{m} I_{\Delta^d(y-\hat{\mu})}(\lambda_j)\right\} - \frac{2d}{m}\sum_{j=1}^{m}\log(\lambda_j) \tag{2.4}$$

Where: $I_{\Delta^d(y-\hat{\mu})}(\lambda_j)$ is the periodogram of $\Delta^d(y-\hat{\mu})$. For fractional differences, to be determined, it is assumed that $\{y_t\}$ is given by a process similar to equation (2.1). It turns out that the first sample observation y_1 is a reliable mean estimator in the case of large values of $\bar{y}$, while the usual arithmetic mean $\bar{y}$ helps ensure a significant task for small coefficient values of d. In this way, [18] suggests putting forward the subsequent weighted estimator, such as:

$$\hat{\mu}(d) = v(d)\bar{y} + (1 - v(d))y_1 \tag{2.5}$$

$$v(d) = \begin{cases} 1, & d \le 0.5 \\ \dfrac{1+\cos(4\pi d)}{2}, & 0.5 < \mathrm{d} < 0.75 \\ 0 & \mathrm{d} \ge 0.75 \end{cases} \tag{2.6}$$

For the purpose of attaining, a feasible procedure, he considers two necessary steps, the first of which serves to determine an estimator of $\hat{d}$ independent from μ in order to get an estimator of the constant: $\hat{\mu} = \hat{\mu}(\hat{d})$. As for the second step, the slope and Hessian of $R_E(m,d)$ are used to compute the feasible estimator as follows:

$$\hat{d}_{2ELW} = \hat{d} - \frac{R'_E(m,\hat{d})}{R''_E(m,\hat{d})} \tag{2.7}$$

Besides, [18] demonstrates shows that the two-step ELW estimator (2ELW) proves to be consistent registering the same limiting distribution as the LW and ELW estimators under $-0.5 < d < 2$. Similarly, and as indicated as shown by [14], if an unknown mean (initial value) appears to undergo certain change by its sample average, simulations suggest that the ELW estimator is inconsistent for $d>1$. It is actually for this reason that we undertake to apply the 2ELW. In addition, [14] resort to modify the ELW objective function in a bid to estimate the mean by means of combining two estimators: the sample average and the first observation. He indicates the resulting estimator as being a two Stage Exact Local Whittle (2ELW). Applying the tapered estimator of [30] in its first stage, the 2ELW estimator, bears the same $N\left(-\frac{1}{2},2\right)$ limit distribution for $N\left(-\frac{1}{2},2\right)$ and is consistent when $d > \frac{1}{2}$.

Furthermore, the 2ELW estimator finite sample performance appears to inherit the 2ELW estimator, desirable properties. Moreover, it can also be computed with prior data de-trending (2ELWd) as in [14].

2.2. GARCH Models

The Autoregressive Conditional Heteroscedasticity (ARCH) process proposed by Engle [20] and the generalized ARCH (GARCH) by Bollerslev and Wright [21] 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.

Analysis of the relationship between numbers of cases among studied countries knowledge of the dependence structure between these two series. A flexible copula is a representation of the dependency structure which connects the margins for a distribution function with several variables. Theorem states that the joint distribution of two continuous random variables X and Y, F_{XY} (x, y), with marginal functions F_X (x) and F_Y (y), is characterized by a copula function C [22].

In finance and economic literature modeling multivariate distributions is an important issue. To avoid a high level of complexity, we will use bivariate distribution copula method to model the dependence between two variables. Generally, there are three main bivariate copulas families; elliptical (Gaussian and Student), Archimedean (Clayton and Frank) and EVT copulas (Gumbel). The symmetric dependency on both tails is examined by the elliptical family while Clayton copula captures the left tail and the right tail is captured by the Gumbel copula. In our case, we use five Archimedean copulas (Frank, Clayton, Joe, bb4 and bb7) and two EVT copulas (Gumbel). For all these copulas Table 1 provides the functional form, dependence parameters and Kendall tau.

Table 1: Distribution and characteristics of several copula models

Copula	Distribution	Parameter	Kendall tau
Frank	$C(u_1,u_2;\alpha) = -\frac{1}{a}\ln(1 + \frac{(e^{-au_1}-1)(e^{-au_2}-1)}{(e^{-a}-1)}$	$0 < \alpha < \infty$	$\frac{\alpha}{\alpha+2}$
Clayton	$C(u_1,u_2;\alpha) = (u_1^{-\alpha} + u_2^{-\alpha} - 1)^{-1/\alpha}$	$\alpha \in [-1,\infty) \setminus \{0\}$	$\frac{\alpha}{\alpha+2}$
Joe	$C(u_1,u_2;\alpha) = 1 - ((1-u_1)^\alpha + (1-u_2)^\alpha - (1-u_1)^\alpha(1-u_2)^\alpha)^{1/\alpha}$	$\alpha \geq 1$	
bb4	$C(u_1,u_2;\theta,\delta) = (u_1^{-\theta} + u_2^{-\theta} - 1 - \left[(u_1^{-\theta}-1)^{-\delta} + (u_2^{-\theta}-1)^{-\delta}\right]^{-\frac{1}{\delta}})^{-1/\theta}$	$\theta \geq 0$ and $\delta > 0$	
bb7	$C(u_1,u_2;\theta,\delta) = 1 - (1 - [(1-(1-u_1)^\theta)^{-\delta} + (1-(1-u_2)^\theta)^{-\delta} - 1]^{-\frac{1}{\delta}1/\theta}$	$\theta \geq 1$ and $\delta > 0$	
Gumbel	$C(u_1,u_2;a) = \exp(-[(-\ln u_1)^a + (-\ln u_2)^a]^{\frac{1}{a}})$	$a \in [1,\infty)$	$1 - 1/a$

2.3. DCC multivariate GARCH models

We employ the conditional correlation matrix R_t of the returns of markets i and j and the multivariate conditionnel variance H_t.

The DCC model developed by Engle [17] includes a two-stage estimation of the conditional covariance matrix H_t. In the first stage, the univariate volatility models are fitted for each of the numbers of deaths and this way we obtain the estimations of $\sqrt{h_{ii,t}}$. In the second stage, numbers of deaths residuals are transformed by their estimated standard deviations from the first stage. That is, $u_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$, where $u_{i,t}$ is used to estimate the parameters of the conditional correlation.

The DCC model used in this study includes two stages in the estimation process to maximize the log-likelihood function. Hence, this function can be written as the sum of one volatility part and one correlation part.

The first stage gets the most appropriate volatility parameter of country $\hat{\Theta}$. The second stage $\hat{\Theta}$ for the estimation of the most adequate correlation coefficient $\hat{\Phi}$. Under certain regularity conditions, the consistency of the first stage should guarantee the reliability of the second stage.

2.2. Asymmetric DCC Model (A-DCC)

A part from the DCC model, we also consider it useful to appeal to the asymmetric DCC (A-DCC) specification of Cappiello et al. (2006). The ADCC model is often applied to introduce asymmetries revolve in the correlation dynamics. Such a choice is often applied made because the DCC pertaining correlations usually follow a scalar BEKK-like process which wakes it too restrictive to apply the model on the entirely of series at once. In addition to the DCC, the ADCC model is also subject of application. The ADCC (1,1,1)[1] model is expressed as:

$$\sigma_t^{\delta} = w + \alpha_1 |\varepsilon_{t-1}|^{\delta} + \gamma_1 |\varepsilon_{t-1}|^{\delta} I_{[\varepsilon_{t-1}<0]} + \beta_1 \sigma_{t-1}^{\delta} \tag{2.10}$$

$$Q_t = (1-\theta_1-\varphi_1)\bar{Q} - r_1\bar{N} + \theta_1(u_{t-1}u'_{t-1}) + \tau_1(n_{t-1}n'_{t-1}) + \varphi_1 Q_{t-1} \tag{2.11}$$

3. Results

3.1. Data

The data used in this paper are the daily closing numbers of two cases and deaths

1. DCC is a special version case of ADCC when τ1 = 0.

indexes, namely total cases and total deaths. The data concerning the Italy, France and United Kingdom indexes are available from the Centers for Disease Control and Prevention. All data are denominated in number of people. There are 100 observations from January 22, 2020 to April 30, 2020.

In order to estimate the conditional variance and the conditional correlation coefficient, we need to preliminarily analyze the descriptive statistics of the sample. Table 2 displays the descriptive statistics for the samples of six series (total cases and total deaths for three countries, namely, Italy, France and United Kingdom).

Table 2: The descriptive statistics of the total cases and total deaths

	Italy		*France*		*UK*	
	T cases	*T deaths*	*T Cases cases*	*T deaths*	*T cases*	*T deaths*
T	100	100	100	100	100	100
Mean	61396.13	7607	40934.83	5078.76	31763.62	4679.93
Std. dev.	73897.81	9820.87	58873.34	8093.58	51255.65	8022.167
Skewness	0.741 (0.00)	0.885 (0.00)	1.166 (0.00)	1.328 (0.00)	1.471	1.567
kurtosis	-1.09 (0.03)	-0.836 (0.09)	-0.246 (0.62)	0.154 (0.76)	0.746	1.013
J.B	14.10 (0.00)	15.98 (0.00)	22.92 (0.00)	29.49 (0.00)	38.418	45.238
ARCH	0.542**	0.621**	0.713**	0.628**	0.429**	0.832**

In the total cases, the number of cases mean is important in Italy (61396.13) than the France and U.K. In Italy, also the number of deaths in mean is important than the others countries studied. Meanwhile, the standard deviation shows that the total deaths in Italy has the highest risk (Std. dev = 9820,87). The total cases in Italy takes the high risk (Std. dev = 73897.81). 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 Italy, France and U.K total cases and deaths. The excess 3 kurtosis coefficients exhibit a leptokurtic distribution of the three countries 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 [20].

3.2. Long Memory Dependency and the Outbreak Ebola Virus

Firstly, the LW estimators of the long memory parameters for the periods as reported in Table 2 are lower than 0.5 for the studied period. This result indicates that the long memory dependency in the outbreaks period is the highest. This may be due to the shocks and the breaks that occurred in the European countries during the recent period. A possible explanation is that the invasive occurrences in the total cases and total deaths during the outbreaks lasted for extended periods and increased the long memory property as the volatility process responded to the shocks and the breaks asymmetrically and gradually as pointed out by Andersen *et al* [23].

Table 3: Estimation of the long memory parameters

	Italy		*France*		*UK*	
	T cases	*T deaths*	*T Cases cases*	*T deaths*	*T cases*	*T deaths*
LW	0.428	0.379	0.327	0.322	0.313	0.276
2LW	0.627	0.813	0.523	0.698	0.586	0.583
2ELWd	0.529	0.648	0.328	0.739	0.821	0.691

Note: LW, 2ELW and 2ELWd indicates respectively Local Whittle, 2 Stage Exact Local Whittle and Exact Local Whittle with detrending.

Table 3 indicates that the long memory property in the Italy period appears to be slightly higher than that in the France and U.K. This may be due to the more asymmetric number of deaths volatility in the outbreaks period. It can be seen that the volatility is highly persistent in all countries during the epidemic corona virus.

Based on table 3, the LW do actually prove that $0.5 \leq \hat{d} \leq 1$. Indeed, this consists in a long-memory process case through still stationary, with a slow or smooth decay in the catching-up process.

In reality, this coincides with the "stochastic divergence" case liable to comparison with the initial deterministic divergence case. Regarding the 2ELW estimator, it has been demonstrated that $0.5 \leq \hat{d} \leq 1$, corresponding to a long memory process case, which is non-stationary through still reverting. In such a case, the process is featured with high persistence, whereby any distant past output difference would still have a long-lasting present inference. With respect to the 2ELWd estimator, it has also been demonstrated that $0.5 \leq \hat{d} \leq 1$ regarding the entirety of studied cases, except for France (total cases).What noting also, the number of deaths highest values are important than the total's cases (respectively for Italy and France), highlight well the persistent of shocks in the number of corona virus increased deaths and its contagion. We note that the persistence of the corona-virus is important for the number of deaths than the number of cases affected across the three countries studied.

3.3. Effects of the 2019-2020 European corona virus

We now consider the contagion effects of the 2019-2020 European corona-viruses and the volatility transmission from the Italy to the rest of the European during the outbreaks corona 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 corona virus. We pay special attention to the transmission of shocks and volatility. Our estimated model for the whole period shows that the linkage between the Italy numbers of cases, the France and U.K 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 4 reports the results.

Table 4: The Criterion Copula Parameters

Parameter	Italy-France				Italy-U.K		
	LL	AIC	Rank		LL	AIC	Rank
Normal	-89.427	123.024	2		-81.321	94.231	2
Frank	2.134	-3.127	1		1.298	2.134	1
BB4	-94.237	197.298	3		-93.124	98.231	3

Table 4 indicates that under the likelihood and AIC criterion, the better copula explaining the structure dependence between Italy and France is Frank and for the Italy- U.K number of deaths couple is Frank. The better copula is selected since the lower value of the likelihood and AIC criterion.

Our findings summarize the copula estimation results. They show that the Frank copula is the best one in three out of six cases. For the Italy-France number of cases pair, the results suggest the Frank copula as the best fitting model. Notice here that the Frank copula has more observations in the Gaussian copulas, while the Frank copula is more suitable for capturing the dependence among series. Combining the findings, we see that the dependence between Italy and U.K number of deaths, modeled by Frank copula models, is positive for two considered pairs. Our empirical evidence is thus not consistent with the findings of the majority of previous studies using data during the period of the recent outbreak corona-virus.

We find that the dependence between the Italy- index and France (2.134) is less than the dependence between the Italy index and U.K (1.298). This result can be explained by the contagion deaths fact that European countries are based in deaths in Italy. The most deposit of number of deaths derived from oil that causes the epidemics excess which number of deaths suffer a lot. The same result is confirmed by the correlation and spearman coefficient.

We find β_c being bigger than β_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.

Table 5: Results of the MGARCH-DCC (1,1) models

	Total Cases			*Total Deaths*		
	Italy-France	*Italy-UK*	*France-U.K*	*Italy-France*	*Italy-UK*	*France-U.K*
c_2	0.117231789*	0.128542994*	0.1499351967*	0.159839667*	0.201768231	0.232419657*
c_2	0.1307493286	0.1322234674	0.1200698695*	0.191229141*	0.201768231*	0.19326348*
w_1	0.0213699808	0.0187536784	0.0163466168	0.036867345	0.042214452	0.041885554
w_2	0.0682874708	0.0641069355	0.0021581189	0.034129198	0.015601001	0.032041487
α_1	0.0430030858	0.0388492727	0.0099182558	0.111051133	0.018783338	-0.060956679
β_1	0.0516604014	0.0513174527	0.0107754859	0.163094159	0.248146891	0.199132455
β_1	0.5198406988	0.5648221277	0.5399452047	0.255481697	0.248146891	0.406024938
β_2	0.4256461490	0.4580115215	0.9223908139	-0.002039403	-0.093376042	-0.023926613
a_m	0.2021582063	0.1976269505	0.2380426412	0.299200724	0.305470908	0.174208100
α_c	0.2021582063	0.0000000003	0.3943492143	0.170393224	0.260975239	0.113725774

Notes: * indicate the significance level at 5%.

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 0.40 being greater than α_c, 0.31 under restriction that coefficients and $\alpha_c + \beta_c < 1$ is 0.70. 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 Italy, France and U.K. 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 European countries.

Table 6: Results of the MGARCH-ADCC (1,1) models

	Total Cases			*Total Deaths*		
	Italy-France	*Italy-UK*	*France-U.K*	*Italy-France*	*Italy-UK*	*France-U.K*
θ_1	0.411 (0.00)	0.537 (0.00)	0.428 (0.00)	0.638 (0.00)	0.481 (0.00)	0.374 (0.00)
τ_1	0.728 (0.00)	0.342 (0.23)	0.421 (0.87)	0.371 (0.23)	0.527 (0.00)	0.611 (0.00)
τ_1	0.98 (0.07)	-0.24 (0.99)	-0.387 (0.82)	0.128 (0.00)	0.315 (0.00)	0.421 (0.00)
BIC	4213.24	5217.35	4234.28	4718.31	4278.38	8291.82

Table 6 shows the empirical results of the entire sample period. The estimates at the parameter of standardized residuals (θ_1) and innovation in the dynamics of the conditional correlation matrix (φ_1) are both statistically significant at 1% level, whereas the parameter of the asymmetric term (τ_1) is statistically significant at 5% level. Thus, the conditional correlation of the total cases is influenced more significantly by negative innovations than by positive ones. Table 6 shows the empirical results by cases and deaths. We infer that the parameter of the asymmetric term τ_1 for all cases is not statistically significant at conventional levels, and statistically significant at 1% level for total deaths. These results suggest that the interdependent relationship the number of deaths between Italy, France and U.K number of deaths and Brent oil price has evolved since the corona-virus epidemic came into effect.

WHO encourages all countries to strengthen their surveillance for severe acute respiratory infections (SARIs), carefully review any unusual presentations of SARS or pneumonia cases, and inform WHO of any suspected or confirmed case of infection with a novel corona virus.

Countries are encouraged to continue to strengthen their preparedness for health emergencies, in accordance with the International Health Regulations (2005).

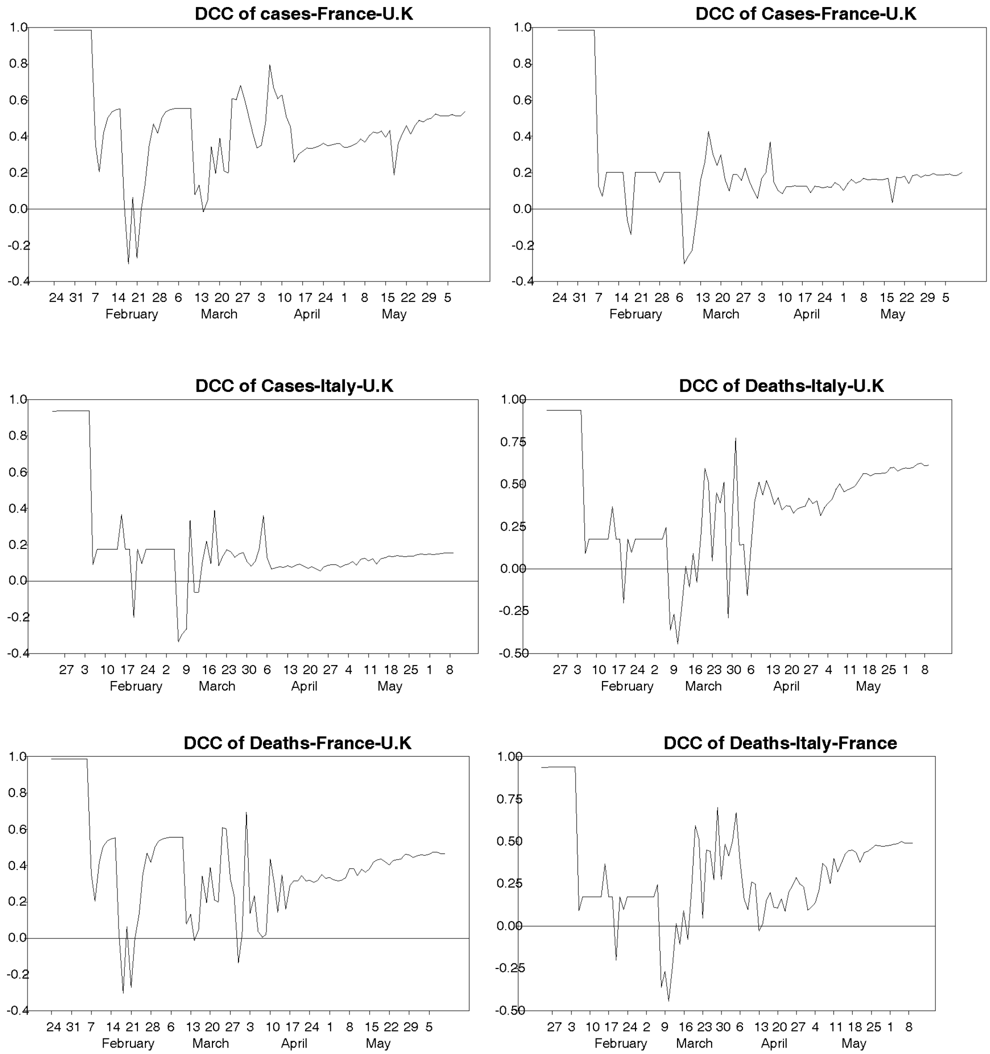

Figure 1: A-Dynamic Correlation Coefficients of returns between countries

Looking at the figures of the case numbers, we note the stability of the DCC from April for the two couples (Italy-U.K) and (France-U.K). In contrast, these last two couples have shown that the dynamic conditional correlations between France and the UK are important.

Concerning the figures of the DCC of the number of deaths, we note the existence of contagion for the three couples studied. This tells us, the persistence of the corona virus across these three countries indicates a high probability of contagion. 2019-nCoV can cause respiratory illness and spread from person to person, usually as a result of close contact with an infected patient, for example in a home, workplace, or in a health facility.

Following the analysis above, we will analyze the total cases. As a starting point, all the total cases series of countries under investigation depend on their first lags. Next, we document the evolution of the correlation in the DCC model represented by α_c and β_c. The results show that the volatility shocks from the Italian country have a little effect on the numbers of deaths of studied countries. We can identify a significant link between the Italia, France and U.K number of cases during this period.

The parameters for the lagged variance and shock-squared terms are highly significant during outbreak corona virus period. The parameters show also that the sum ($\alpha_c + \beta_c$) is close to unity for all of the cases, which indicates a high persistence of volatility and contagion of corona virus.

There is a strong consensus in the existing literature that correlations among countries show an increasing trend during the epidemic period. So as to investigate the relevance of the outbreaks contingent theories, first, we focus on the cross-market correlation among total cases during the outbreak period. A significant shift in the correlation structure is apparent. It is evident that the correlations are fairly higher during epidemic period. Moreover the Local Whittle method also establishes the interdependence between the markets during the epidemic period.

The significant increase of the correlation in the DCC is found for the pairs of Italy-France and Italy- U.K which confirm the cross-market contagion. Looking at the coefficients (β_c) and (α_c) during the epidemic corona virus for a pair of France-U.K, we conclude that there is no contagion coming directly from the Italy number of deaths.

Concerning the parameters of ADCC during the epidemic corona virus related to the previous pairs, the coefficients are significant and indicate a higher level of correlation which suggests the existence of a contagion between Italy and European countries.

Although we still need to learn more about how 2019-nCoV affects individuals, so far older people and people with other illnesses (such as diabetes and heart disease) appear to be at higher risk for risk of developing a severe form of the disease.

4. Conclusion

Our paper has examined the international transmission of the epidemic Corona virus. As a starting point we have employed Local Whittle method to analyze the effects of this virus in the European countries' on the long memory dependency in the volatility process of the number of deaths caused by corona virus. The estimation results show that the long memory dependency in the volatility process is most significant during the epidemic, especially in European countries which experienced significant shocks and breaks associated with the epidemic.

Then, we have analyzed the contagion effect of outbreak corona virus using a A DCC multivariate GARCH model according to three countries: Italy, France, and U.K. Volatility spillovers are found only in the studied period. For the European countries', highly significant, increasing correlation has been observed during the epidemic period, which is a clear evidence of contagion death.

Finally, using a DCC bivariate GARCH model, we have estimated two pairwise models. During the outbreak corona virus, the France and U.K countries were affected by a strong contagion coming directly from the Italy number of deaths. For the U.K country, the shocks did not come directly from the Italy. This indicates that the Italy country was partially integrated into the European 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 series pairs in times of epidemics.

Corona-viruses are a large family of viruses that can be pathogenic in animals or humans. It is known that in humans, several corona-viruses can cause respiratory infections ranging from the common cold to more serious illnesses such as Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS). The last corona-virus that was discovered is responsible for corona-virus disease 2019 (COVID-19).

Conflict of interest statement

We declare that we have no conflict of interest.

Acknowledgment

The authors wish to thank all the officers, doctors in World Health Organization for their cooperation during sampling and collection the number of deaths.

References

Baize S, Pannetier D, Oestereich L, Rieger T, Koivogui L, Magassouba N, et al. Emergence of zaire ebola virus disease in Guinea: Preliminary report. *N Engl J Med* 2014; 371: 1418-1425.

World Health Organisation. Disease outbreak news. Geneva: WHO; 2014.

Dowell SF, Mukunu R, Ksiazek TG, Khan AS, Rollin PE, Peters C. Trans-mission of Ebola hemorrhagic fever: a study of risk factors in family members, kikwit, democratic republic of the congo 1995. *J Infect Dis* 1999; 179: S87-S91.

Formenty P, Libama F, Epelboin A, Allarangar Y, Leroy E, Moudzeo H, et al. Outbreak of Ebola hemorrhagic fever in the Republic of the Congo, 2003: a new strategy? *Med Trop (Mars)* 2003; 63: 291-295.

Leroy EM, Rouquet P, Formenty P, Souquière S, Kilbourne A, Froment JM, et al, Multiple Ebola virus transmission events and rapid decline of central African wildlife. *Science* 2004; 303: 387-390.

Nkoghe D, Kone ML, Yada A, Leroy E. A limited outbreak of Ebola haemo-rrhagic fever in Etoumbi Republic of Congo 2005. *Trans R Soc Trop Med Hyg* 2011; 105: 466-472.

Breman J, Piot P, Johnson K, White M, Mbuyi M, Sureau P, et al. The epidemiology of Ebolahemorrhagic fever in Zaire 1976. In: Pattyn SR, editor. *Ebola virus haemorrhagic fever*. Amsterdam: Elsevier; 1978: p. 85-97.

Ferrari MJ, Bjørnstad ON, Dobson AP. Estimation and inference of R0 of aninfectious pathogen by a removal method. *Math Biosci* 2005: 198: 14-26.

Khan AS, Tshioko FK, Heymann DL, Le Guenno B, Nabeth P, Kerstiëns B, et al. The reemergence of Ebola hemorrhagic fever, Democratic Republic of the Congo 1995. *J Infect Dis* 1999; 179: S76-S86.

Chowell G, Hengartner NW, Castillo-Chavez C, Fenimore PW, Hyman JM. The basic reproductive number of Ebola and the effects of public healthmeasures: the cases of Congo and Uganda. *J Theor Biol* 2004; 229: 119-126.

Okware S, Omaswa F, Zaramba S, Opio A, Lutwama J, Kamugisha J, et al. An outbreak of Ebola in Uganda. *Trop Med Int Health* 2002; 7: 1068-1075.

Legrand J, Grais RF, Boelle PY, Valleron AJ, Flahault A. Under-standing the dynamics of Ebola epidemics. *Epidemiol Infect* 2007; 135: 610-621.

Forbes KJ, Rigobon R. No contagion, only interdependence: Measuring stock market comovements. *J Finance* 2002; 57: 2223-2261.

Robinson PM: Log-periodogram regression of time series with long range dependence, Annals of Statistics, 1995, 23, 1048-1072.

Proceedings of the First World Congress of the Bernoulli Society.vol.1. Utrecht:VNU Science Press;1987,p.67-74.

Taqqu MS, Teverovsky V. Robustness of Whittle type estimators for time series with long-range dependence. *Stochastic Models* 1997; 13: 723-757.

Taqqu MS, Teverovsky V. On estimating the intensity of long-range dependence in finite and infinite variance time series. Practical guide to heavy tails. Boston, MA: Birkhauser; 1998: p. 177-217.

Engle R. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J Bus Econ Stat* 2002; 20(3): 339-350.

Shimotsu K.: Exact Local Whittle Estimation of Fractional Integration with Unknown Mean and Time Trend. Econometric Theory, 2008, forthcoming.

Khan AS, Tshioko FK, Heymann DL, Le Guenno B, Nabeth P, Kerstiëns B, Fleer-ackers Y, Kilmarx PH, Rodier GR, Nkuku, O: The reemergence of Ebola hemorrhagic fever, Democratic Republic of the Congo 1995. J. Infect. Dis., 1999, 179, S76–S86..

Engle RF. Autoregressive conditional heteroskedasticity with estimates of the variance of UK inflation. *Econometrica* 1982; 50: 987-1008.

Bollerslev T, Wright JH. Semiparametric estimation of long memory volatility dependencies: the role of high frequency data. *J Econ* 2000; 98: 81-106.

Sklar A. Fonctions de Répartition á n Dimensions et Leurs Marges, 8. Paris: Publications de l'Institut Statistique de l'Université de Paris; 1959: p. 229-231.

Andersen TG, Bollerslev T, Diebold FX, Labys P. The distribution of realized stock return volatility. *J Financial Econ* 2002; 61: 43-76.

WHO China's latest SARS outbreak has been contained, but biosafety concerns remain – Update 7 » [archive], sur WHO (consulté le 30 mars 2020)

Wallinga J, Teunis P, « Different epidemic curves for severe acute respiratory syndrome reveal similar impacts of control measures », Am.J.Epidemiol., vol. 160, no 6, 2004, p. 509–16 (PMID 15353409, DOI 10.1093/aje/kwh255, lire en ligne [archive])

Timeline: SARS outbreak » [archive], CNN, 24 avril 2003 (consulté le 20 avril 2015)

Coronavirus never before seen in humans is the cause of SARS Unprecedented collaboration identifies new pathogen in record time [archive] Geneva, 16 April 2003, www.who.int. Retrieved 22 January 2020.

Robinson PM: Log-periodogram regression of time series with long range dependence, Annals of Statistics, 1995, 23, 1048-1072.

Shimotsu K.: Exact local Whittle estimation of fractional integration with unknown mean and trend. Econometric Theory, 2010, 26, 501–540.

Shimotsu K, Phillips PCB: Exact local Whittle estimation of fractional integration, Annals Statistics, 2006, 33, 1890-1933.