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Studying the relationship among vaccination for Covid-19, new tests and new deaths in USA: A DCC-EGARCH approach

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Abstract
This paper examines the time-varying conditional correlations among new deaths because of covid-19, new tests for covid-19 and new vaccination for covid-19. We apply a trivariate dynamic conditional correlation (DCC) EGARCH model to capture potential contagion effects between the markets for the period 2020-2022. Empirical results reveal contagion. Findings have crucial implications for policymakers who provide regulations for the above derivative markets and for investors, who apply massive strategies to convince the general public to be vaccinated.

Keywords: Covid-19, Vaccination, Public Health, DCC-EGARCH model, Contagion, Dynamic Conditional Correlation

Introduction

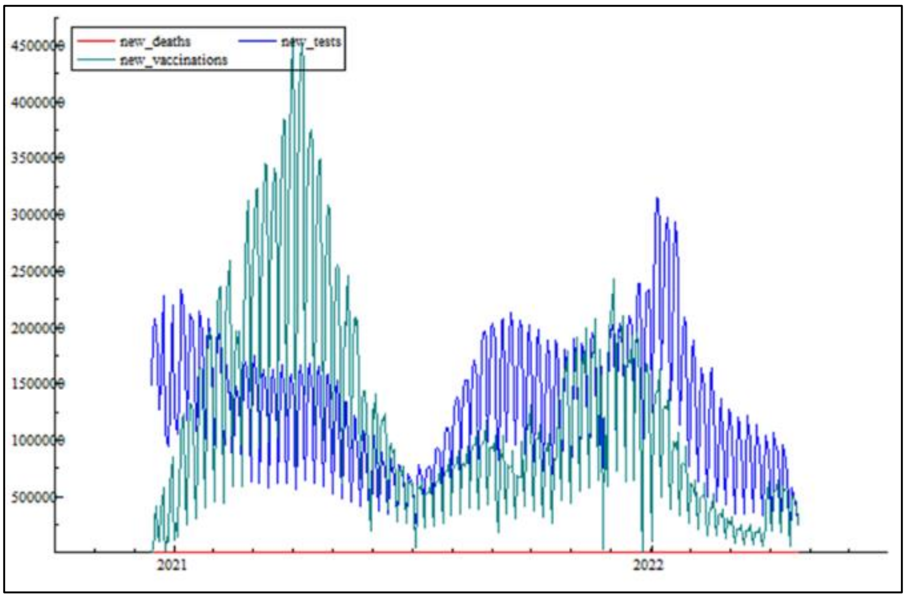
This paper investigates the volatility transmission among new deaths because of covid-19, new tests for covid-19 and new vaccination for covid-19 in the USA for the period 2020-2022. We extend the correlation analysis of Forbes and Rigobon (2002) by considering the Dynamic Conditional Correlation Exponentially GARCH (DCC-EGARCH) of Nelson (1991) [28].
The main objectives of this paper are to address the following questions which are not under-researched in the current literature regarding the under investigation markets. Do Dynamic Conditional Correlations (DCCs) among the three markets exist? Are the DCCs volatile? How do those DCCs evolve over time? Are there any contagion effects?
The rest paper is structured as follows Section two presents the current literature for COVID-19. In Section three, we see the methodology and the data. Section four shows the empirical results, whilst Section five gives the conclusions.
Figures 1 presents the actual series of the markets. We can recognize a downward trend for all markets.

Literature Review

The covid-19 vaccination hesitancy has been explored by numerous researchers (Cohen, 2020; Cutler and Summers, 2020; Bertoncello, *et al*., 2020; Williams, *et al*., 2020; Kempe, *et al*., 2020; Freeman, *et al*., 2020; Gatwood, *et al*., 2020) [6, 7, 5, 35, 18, 12, 1]. Additionally, we notice the lowest acceptance of covid-19 vaccine in some countries (France, USA). Various factors are responsible for the covid-19 vaccination hesitancy (Ball, 2020; Kwok, *et al*., 2020; Palamenghi, 2020; French, *et al*., 2020; Agrawal, *et al*., 2020) [4, 22, 30, 13, 1]. There are still many healthcare workers who have hesitancy about the covid-19 vaccination (Johnson, *et al*., 2019; Badur, *et al*., 2020; McAteer, *et al*., 2020) [19, 3, 25].
The implications of vaccination for covid-19 have been explored by various researchers
(Ding, *et al*., 2020; Malik, *et al*., 2020; Khubchandani,, *et al*., 2021; Sallam, 2021) [8, 24, 21, 33], as well as the impact of new tests

(Wang, *et al*., 2020; Fisher, *et al*., 2020; Khubchandani, *et al*., 2020; Murphy, *et al*., 2021; Nguyen, *et al*., 2021) [34, 11, 20, 27, 29]. Additionally, in the literature, the consequences of new deaths have been investigated (Dror, *et al*., 2020; Helmy, 2020; Lazarus, *et al*., 2020; Papagiannis, *et al*., 2020; Gharpure, *et al*., 2021) [9, 16, 23, 31, 15].

There is still a huge gap in the literature regarding the examination of the pandemic. To the best of our knowledge, this is the first empirical research investigating whether covid-19 tests, deaths and vaccines are defined by the same factors.



Source: Our World in Data Database

Fig 1: Actual series of the markets

Model and Data Description

DCC-EGARCH (1, 1) model

To study the time varying conditional correlations between the markets, we describe the dynamics of market logarithmic returns by their first lagged returns, as follows:

First, we apply the EGARCH model, which adopts another natural function to ensure that σ_t^2 remains non-negative, by composing $ln(\sigma_t^2)$ as linear in some functions of time. To accommodate the asymmetric relationship between return and volatility the value of $g(z_t)$ must be a function of both the magnitude and sign of z_t. If $g(z_t)$ is a linear combination of z_t and $|z_t|$, σ_t^2 is given "well-behaved moments" (Nelson, 1991) [28]. This linear combination of $g(z_t)$ is expressed in equation (2).

$$ln(\sigma_t^2) = a_t + \sum_{k=1}^{\infty} \beta_k \, g(z_{t-k}) \quad (1)$$

$$g(z_t) = \theta z_t + \gamma\{|z_t| - E(z_t)\} \quad (2)$$

The variance-covariance matrix of the residuals (Engle, 2002) is defined as follows:

$$H_t = D_t R_t D_t \quad (3)$$

D_t is the conditional variance matrix given by:

$$D_t = diag\left(h_{11t}^{\frac{1}{2}} \dots h_{NNt}^{\frac{1}{2}}\right) \quad (4)$$

R_t is the condition correlation matrix of *N x N* dimension, and is defined as follows:

$$R_t = (\rho_{iit}) = diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) Q_t diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) \quad (5)$$

Where the *N x N* symmetric positive definite matrix $Q_t = (q_{ii,t})$ is given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1}, \quad (6)$$

$\bar{Q}$ is the *N x N* unconditional variance matrix of u_t, and α and β are nonnegative scalar parameters, satisfying $\alpha + \beta < 1$.

The parameters of the DCC-EGARCH model are estimated by using the Full Information Maximum Likelihood (FIML) method with student's t-distributed errors as follows:

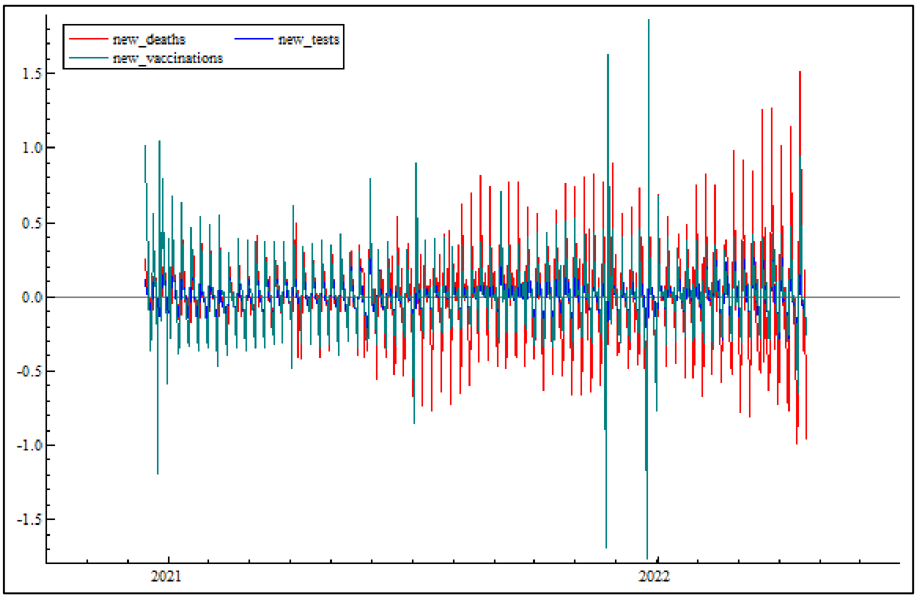
$$\sum_{t=1}^{T}\left[log\frac{\Gamma\left(\frac{v+k}{2}\right)}{[v\pi]^{\frac{k}{2}}\Gamma\left(\frac{v}{2}\right)v-2^{\frac{k}{2}}} - \frac{1}{2}\log(|H_t|) - \left(\frac{k+v}{2}\right) log\left[1 + \frac{\varepsilon_t' H_t^{-1} \varepsilon_t}{v-2}\right]\right] \quad (7)$$

Where *Γ(.)* is the Gamma function, *k* is the number of equations and *v* is the degrees of freedom.

Data Description

For the empirical study, daily data is used for the following variables regarding the COVID-19 pandemic: new_deaths, new_tests and new_vaccinations. The under examination period spans from 14th December 2020 until 23rd April 2022, leading to a sample of 496 observations. We extracted the data from *Our World in Data Database*. We produce markets' logarithmic returns by using the following equation: $r_t = log(p_t) - log(p_{t-1})$, where p_t is the price of the market on day *t* and p_{t-1} the price of the market on day *t-1*.

Figures 2 displays the actual series of all market logarithmic returns. By contacting a visual inspection of logarithmic returns' trend, we observe the heteroskedasticity phenomenon, rationalizing the use of the dynamic conditional correlations in a trivariate EGARCH (1,1) framework.



***Source*:** Our World in Data Database

Fig 2: Actual series of the logarithmic returns of the markets

Empirical Results

Section is divided to five subsections. Sub-section 1 presents the results of the DCC-EGARCH model. Sub-section 2 shows the estimations for average correlations. Sub-section 3 presents an explicit analysis based on dynamic conditional correlations (DCCs). Sub-section 4 states the diagnostic tests.

Empirical Results of the DCC-EGARCH (1, 1) model

In table 1, we observe the estimated values for mean equation and univariate EGARCH (1, 1) model. The mean equation presents significant μ value for all markets. Moreover, variance equation demonstrates significant ω value for the three under investigation markets. ARCH (a) and GARCH (b) terms are highly significant except for the ARCH term of new_tests. Theta 1 is highly significant for all the markets. Theta 1 has negative values for all markets indicating that the volatility is decreasing after a positive shock. In addition, all the three markets present highly significant Theta 2. Theta 2 has positive values for new_deaths and new_vaccinations showing that volatility is increasing after an adverse shock.

Table 1: Estimates of univariate EGARCH (1, 1) model

	New_Deaths	New_Tests	New_Vaccinations
constant *(μ)*	-0,085590***	-0,020326***	-0,011422**
t-Statistic	-7,157	-4,849	-2,109
p-Value	0,0000	0,0000	0,0354
constant (ω)	-1,639647***	-4,378161***	-3,155521***
t-Statistic	-7,457	-52,13	-21,74
p-Value	0,0000	0,0000	0,0000
ARCH *(Alpha1)*	0,913216**	13,342017	-0,596121***
t-Statistic	2,769	0,9912	-3,017
p-Value	0,0058	0,3221	0,0027
GARCH *(Beta1)*	0,887508***	0,103523*	0,799083***
t-Statistic	37	1,458	5,032
p-Value	0,0000	0,1454	0,0000
EGARCH *(Theta1)*	-0,336322***	-0,087655*	-0,955503***
t-Statistic	-5,973	-1,094	-9,338
p-Value	0,0000	0,2746	0,0000
EGARCH *(Theta2)*	0,039164*	-0,079134*	0,173634**
t-Statistic	1,851	-1,131	2,071
p-Value	0,0647	0,2587	0,0389

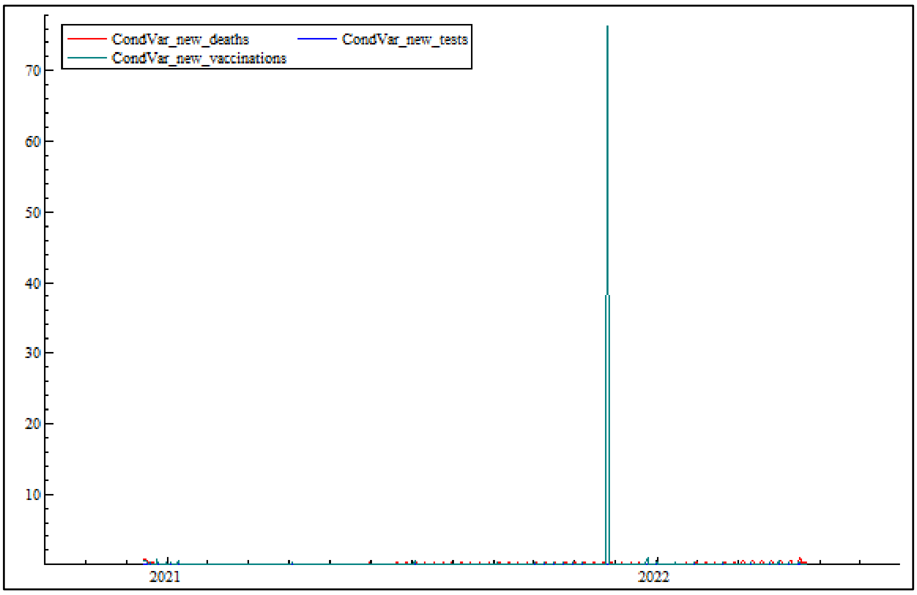
***Source*:** Our World in Data Database

Table 2 presents the normality test results for the univariate EGARCH (1, 1) model. Results indicate normal distribution for the three markets regarding the statistically significant skewness, Excess Kyrtosis and the Jarque-Bera test statistics. In figure 3, we see the estimated of conditional variances for all markets. The visual inspection of the figure shows that all markets demonstrate strong ups and downs over time. We observe an extreme spike in November 2021 for new_vaccinations.

Table 2: Normality Test of univariate EGARCH (1, 1) model

	New_Deaths	New_Tests	new_vaccinations
Skewness	-0,78478***	-1,0255***	-0,94441***
t-Statistic	7,1497	9,3427	8,6040
p-Value	8,6991e-013	9,3903e-021	7,7010e-018
Excess Kurtosis	1,0615***	4,4575***	12,316***
t-Statistic	4,8452	20,345	56,214
p-Value	1,2651e-006	5,1113e-092	0,0000
Jarque-Bera	74,052***	496,57***	3202,1***
p-Value	8,3141e-017	1,4838e-108	0,0000

***Source*:** Our World in Data Database



***Source*:** Our World in Data Database

Fig 3: Conditional variances for the markets of the univariate EGARCH (1,1) model

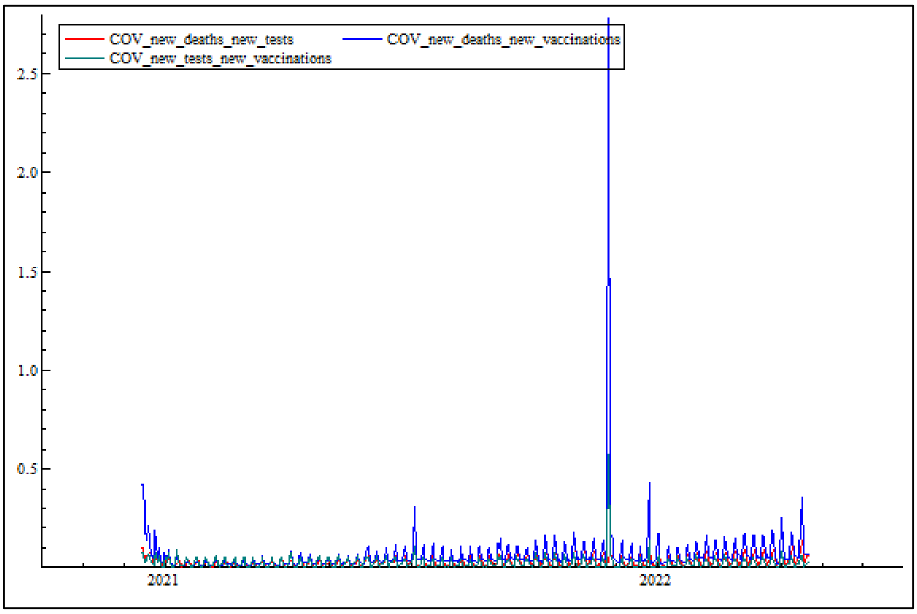
In table 4, we see the results of the estimated trivariate DCC model. DCC model results indicate statistically significant α and β parameters, showing strong ARCH and GARCH effects, suggesting that the markets are integrated. Additionally, the estimated degrees of freedom (v) and the log-likelihood are stated.

In figures 4, we observe the conditional covariances. Results show positive values for all the conditional covariances. We can see an extreme spike in November 2021 for the pair of markets new_deaths – new_vaccinations.

Table 3: Estimates of the trivariate DCC-EGARCH (1,1) model, degrees of freedom, log-likelihood

	New_Deaths- New_Tests- New_Vaccinations
alpha *(α)*	0,011078***
t-Statistic	3,684
p-Value	0,0003
beta *(β)*	0,988912***
t-Statistic	190,8
p-Value	0,0000
degrees of freedom (*df*)	10,248355***
t-Statistic	4,557
p-Value	0,0000
log-likelihood	860,431

***Source*:** Our World in Data Database



Source: Our World in Data Database

Fig 4: Conditional covariances for the pairs of markets of the trivariate DCC-EGARCH (1, 1) model

Estimates of the Average Correlations for DCC-EGARCH (1, 1) model

Table 5 presents the estimated average correlations of the trivariate EGARCH (1,1)-DCC model. We observe that all the average correlations are statistically significant. Additionally, all the average correlations for the pair of markets have positive values.

Table 4: Estimates for the average correlations of the trivariate DCC-EGARCH (1, 1) model

	Coefficient	t-Statistic	p-Value
new_tests -new_deaths	0,788424***	10,91	0,0000
new_vaccinations-new_tests	0,636571***	4,515	0,0000
new_vaccinations- new_tests	0,735638***	10,90	0,0000

Source: Our World in Data Database

Economic Analysis of Dynamic Conditional Correlation Coefficients

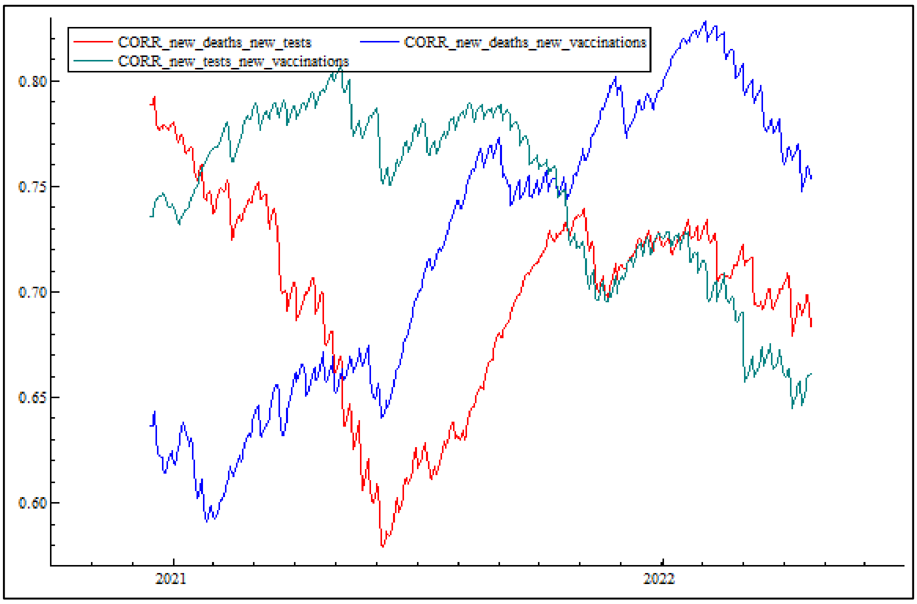
In table 7, we see the descriptive statistics of the dynamic conditional correlations (DCCs) for all the pairs of markets. We observe the lowest min value (0,57894) for the pair of markets new_deaths_new_tests, whilst the pair of markets new_deaths_new_vaccinations present the highest max value (0,828). The pair of markets new_deaths_new_vaccinations has the highest mean value (0,74525). Additionally, the pair of markets new_deaths_new_vaccinations shows the highest std. deviation (0,07021) indicating larger flunctuations for the DCCs. The statistical significant Skewness, Excess Kyrtosis and the Jarque-Bera test statistics reveal that the DCCs for all the pairs of markets are not normally distributed.

Table 5: Descriptive statistics of the DCCs

	CORR_new_deaths_new_tests	CORR_new_deaths_new_vaccinations	CORR_new_tests_new_vaccinations
Min	0,57894	0,59094	0,64514
Mean	0,69816	0,72025	0,74525
Max	0,7923	0,828	0,80659
Std.dev.	0,047799	0,07021	0,041411
Skewness	-0,62155***	-0,21461*	-0,67391***
t-Statistic	5,6625	1,9552	6,1396
p-Value	1,4916e-008	0,050557	8,2748e-010
Excess Kurtosis	-0,29362*	-1,3794***	-0,63846**
t-Statistic	1,3402	6,2961	2,9141
p-Value	0,18019	3,0524e-010	0,0035673
Jarque-Bera	33,650***	43,046***	45,875***
p-Value	4,9328e-008	4,4948e-010	1,0925e-010

Source: Our World in Data Database

Figures 5 present the DCCs for all the pairs of markets. We can clearly recognize only positive values and extreme volatility of the DCCs for all the pairs of markets, indicating contagion effects and a less reliable correlation in mass public strategies.



Source: Our World in Data Database

Fig 5: Dynamic conditional correlations for the pairs of markets of the trivariate DCC-EGARCH (1,1) model

Interestingly, we observe that the pair of markets new_tests – new_vaccinations present positive and persistently high DCCs during sub-periods, foreshadowing interdependence phenomenon (Forbes and Rigobon, 2002).

Diagnostic Tests, Hypothesis Testing and Information Criteria

In table 3, we see the diagnostic tests of the univariate EGARCH (1,1) model. Empirical results indicate the absence of serial autocorrelation

Table 6: Diagnostic tests tests of the univariate EGARCH (1,1) model

	new_deaths	**new_tests**	**new_vaccinations**
Box/Pierce^2 (5)	13,3685	2,09151	2,92688
p-Value	0,0501594	0,8363429	0,7112578

Source: Our World in Data Database

In table 6, we present the estimated hypothesis testing results and information criteria. x^2(6) statistic results show that the null hypothesis of no spillovers is rejected at 1% significance level. In addition, Ljuing-Box test results (Hosking, 1980; Li-McLeod, 1983) provide evidence of no serial autocorrelation, indicating the absence of misspecification errors of the estimated DCC-EGARCH (1,1) model. Moreover, the estimated Akaike, Schwarz, Shibata and Hannan-Quinn information criteria are stated.

Table 7: Diagnostic tests and information criteria of the trivariate DCC-EGARCH (1,1) model

	new_deaths
$x^2(6)$	606,82**
p-Value	0,0000
Hosking^2 (5)	41,3591
p-Value	0,5426249
Li-McLeod^2 (5)	41,3948
p-Value	0,5410590
Akaike	-3,379517
Schwarz	-3,175660
Shibata	-3,383935
Hannan-Quinn	-3,299490

Source: Our World in Data Database

Conclusions

In this article, we investigate the volatility transmission among new deaths because of covid-19, new tests for covid-19 and new vaccination for covid-19 in the USA for the period 2020-2022. We apply a trivariate DCC-EGARCH (1,1) model. To the best of our knowledge, this is the first time in the literature attempting to analyze the volatility transmission among the three under investigation markets by quantifying and measuring potential contagion effects.

By employing the EGARCH-DCC model, we find evidence of statistically significant dynamic conditional correlations for all the pairs of markets. The positive dynamic conditional correlations are of interest to policymakers, who apply massive strategies in order to convince the general public to be vaccinated.

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