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Contagion between selected European indexes during the Covid-19 pandemic

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Abstract

The main aim of this study is to examine dynamic dependence and proof of contagion during the Covid-2019 pandemic. The empirical data are daily prices from six European indexes. The FTSE, DAX and CAC indexes represent the largest and most developed stock markets in Europe, while the Austrian ATX index represents small developed markets. The WIG and BUX indexes represent emerging European markets. This empirical study, based on the Dynamic Conditional Correlation model, which is applied to different pairs of indexes, aims to convince the reader of the increase in the correlation between the time of the pandemic (after 30 December 2019) and the period before the beginning of the pandemic. For all pairs, the mean value of the conditional correlations in the pre-Covid period was statistically below the values in the Covid period. The results indicate contagion in Europe after the outbreak of the Covid-2019 pandemic.

Keywords: *European indexes, pandemic Covid-19, dynamic conditional correlation, contagion*

1. Introduction

The world has faced many medical crises, for example, SARS-COV in 2003, MERS-COV in 2012 and Ebola in 2014. The most serious in terms of its impact on the world is Covid-19. Initial reports of an outbreak started at the end of December 2019 in China. The World Health Organization (WHO) declared Covid-19 a pandemic on March 11, 2020. After this declaration by WHO, countries throughout the world implemented different measures to reduce the spread of the virus. These actions had a significant impact on many social and economic aspects of life. Covid-19 started as a viral outbreak. However, it also created financial contagion in global markets. The main economic result was a slowdown in the global economy. The International Monetary Fund's (IMF) World Economic Outlook (WEO) for 2020 forecasted a negative global growth of -3.0% in April, -4.9% in June, and -4.4% in October.

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In our study, we analyze the effect of the Covid-19 pandemic on selected stock markets from the perspective of financial contagion and compare the extent of exposures. The role of stock markets in price formation and determining true share values makes them important platforms for all market economies. Stock markets possess variables called leading indicators which are essential barometers for economies. Stock prices reflect the arrival of information and the expectations of different market participants. We also observe feedback. The economic development, political stability, and protection of shareholders impact funds invested in the stock markets. Sometimes economic conditions may force investors to liquidate their stock holdings and then deposit them in other financial institutions. The relationship between stock markets and economic growth is reciprocal, regardless of a country's level of development. Stock markets are considered a means of foreign direct investment (FDI) flow. A well-developed financial system, protection of shareholders, and high public governance quality support FDI inflow. This reduces the cost of raising per capita and increases economic growth. However, financial interrelations and trade connections make countries more vulnerable to shocks caused by stock market crashes. During the period of the Global Financial Crisis (GFC) and Covid-19, an increase in cross-market linkages and the propagation of crises was observed. Financial contagion can be understood as an unfavourable situation in financial markets. It allows the transmission of shocks and crises. On the other hand, it makes the transfer of development across two or more interrelated countries possible. Thus, an investigation of financial contagion during quiet periods and periods of crisis might be useful for policymakers. They look at these markets and decide what regulations are necessary.

It is well known that not only asset returns, but also volatility, have an effect on the fundamental components of a company e.g. financial position, profit, loss, and cash flows. In addition, volatility is important with respect to investment decisions. It encourages market participants to change their portfolios and hedging strategies. This is necessary with respect to the desired level of risk reduction. Random fluctuations in asset prices are carefully observed by market participants. Fluctuations in equity markets, caused by investor decisions, usually have an impact on consumption decisions. Nowadays, an important role is played by globalisation. The progress of technological developments and policy deregulations support the integration of national stock markets with regional and global markets. Globalisation plays an important role in the transmission of different shocks from one country or group of countries to other countries. The GFC showed that subsequent events increase the speed and effect of financial contagion on globalised markets. It is well known that inflation, employment and financial variables, such as indexes or interest rates, are transmitted from the US to other markets. On the basis of empirical data, market participants have observed a lower correlation between emerging and developed countries with respect to co-movements of asset prices. Therefore, the negative effects of financial contagion and volatility spillovers are expected to concern this group of economies. Consequently, measures that protect against risks created by various financial, economic, or healthcare events, are needed both in developed and emerging economies. To reduce these risks, market participants try to estimate the foreshocks and the mainshocks. Although the Covid-19 pandemic started as an outbreak, such phenomena as lockdowns, curfews and social distancing occurred as a global event very quickly. In order to reach GDP before the outbreak of Covid-19, many countries introduced stimulus packages and vaccination programs. For our analysis, we used data from selected stock markets in Europe. For developed economies, we chose the UK (FTSE), Germany (DAX), France (CAC) and Austria (ATX). From emerging markets, we utilised data from Poland (WIG) and Hungary (BUX). In doing so, evidence is provided for the most and least developed economies in Europe. In the following sections of the study, we provide a literature review and explain the methodology and econometric models utilised in the empirical calculations. Finally, we summarise the major computational results and their economic and financial implications.

2. Literature review

The Covid-19 pandemic has had a huge impact on stock markets throughout the world. This pandemic in particular has caused contagion effects on international stock markets. Many studies have been concerned with financial market movements during the Covid-19 pandemic. Special attention has been paid to Covid-19, the crisis often referred to as the GFC, the East Asian Financial Crisis 1997, the Russian Crisis (1998) and the Mexican Peso-Devaluation 1994.

One of the first studies on contagion was that of King and Wadhwani [26]. They investigated contagion between the US, UK and Japanese stock markets during the crisis period of October 1987. They built a model in which contagion between markets occurred as the outcome of rational attempts to infer information from price changes on other markets. They found that contagion existed. Moreover, their empirical results supported the thesis that an increase in volatility leads to an increase in the extent of contagion. Contagion effects have been observed not only on stock markets but also for currencies during crisis periods, which is documented in Eichengreen et al. [17].

Corbet et al. [14] analyzed contagion effects with respect to the Covid-19 pandemic. This research concerned the interdependence between the Shanghai stock market and the Bitcoin market. Using hourly data from 11 March 2019 to 10 March 2020 as a basis, the authors detected a strong interdependence between these markets. Therefore, the assets from these markets would not be effective as hedging instruments.

Akhtaruzzaman et al. [2] also investigated how financial contagion occurs for a sample of financial and non-financial firms. Their research was based on firms from China and G7. They used the VARMA(1,1) DCC-GARCH model. The authors utilised data from China and G7 countries to establish whether the chosen firms across these countries displayed a significant increase in conditional correlations between their stock returns. This was especially visible in the case of financial institutions and financial firms.

Using DCC models, Akhtaruzzaman et al. [1] considered the importance of China and the US in the transfer of contagion to South Asia. They established that Chinese and US financial firms supplied more spillovers than they received during the GFC.

Stoupos and Kiohos [30] also proved the extent of stock market interrelations in the Eurozone. They used data from after the end of the 2010 debt crisis and analyzed it with the aid of the fractionally cointegrated vector autoregression (FCVAR) and the realised exponential GARCH model. Their results favour the thesis that there are strong interrelations between financial markets within this area. In addition, they are relatively strong between the main states of the Eurozone.

Taking the GFC into account, Dungey and Gajurel [16] looked at the existence of contagion from the US to the four largest countries from the G7 group (France, Germany, Japan and the UK) and the four largest BRICS countries (Brazil, China, India and Russia) during the GFC. They detected significant contagion effects from the US market to these markets, both developed and BRICS markets. However, the authors established that there is weaker contagion from the US financial sector to the financial sector of both G7 and BRICS countries under consideration.

Baur [7] investigated the impact of the GFC in the financial sector on the real economy. He studied ten sectors in 25 major developed and emerging stock markets. On the basis of weekly prices between 23 October 1979 and 20 October 2009, this study confirmed that the null hypothesis of no contagion is in general rejected in around 70% of all cases. These results imply strong contagion effects between aggregate stock markets and between financial sector stocks. Evidence of contagion between sectors that represent the real economy is not very pronounced.

Bekaert et al. [9] provided evidence of the transmission of the crisis to country-industry equity portfolios in 55 countries at the time of the GFC. Using a three-factor asset pricing framework, they showed systematic contagion from the US market and the global financial market. However, these effects were weak. Strong contagion was detected on the domestic level. In addition, on the basis of empirical results, they conclude that contagion was mostly of a domestic nature and did not flow systematically either from the US or from the global banking sector during the crisis period of 2007–2009.

Goetzmann et al. [25] studied the correlations between equities over the long term and detected heavy fluctuations between them. According to them, the advantages of a diversification strategy are possible due to two factors, namely the increasing number of global markets and a lower correlation across markets. The authors detected significant shifts in the structure of global correlations.

One of the first works on financial contagion is that of Dungey et al. [15]. It provided many tools for testing contagion. These approaches include the correlation analysis of Forbes and Rigobon [23], the VAR method of Favero and Giavazzi [21], the probability approach of Eichengreen et al. [17], and the co-exceedance method of Bae et al. [3].

Forbes and Rigobon's contribution [23] is widely cited. The authors used information about all shocks during the crisis period to test for contagion. They studied the stock market co-movements of 28 stock markets. They tested stock markets for contagion using the effect of the VAR-based strategy during the East Asian crisis of 1997, the 1994 Mexican peso collapse, and the US stock market crash of 1987. They found no contagion during these three crises. However, they detected interdependence between these markets.

Baig and Goldfajn [6] attempted to examine contagion on four markets (the equity, sovereign debt, interest rates and exchange rates) between Asian countries (Indonesia, Korea, Thailand, Malaysia, and the Philippines) during the Asian crisis. Correlations between the time of stability and of crisis time supplied evidence of contagion on foreign debt markets. Applying dummy variables to establish the effects of own-country and cross-border news on these markets, they found the existence of cross-border contagion in two markets (the equity and currency markets). In their contribution on contagion between emerging markets Celik [13] used DCC-GARCH models.

To summarise, the relevant literature has mainly focused on developed markets and has found a high level of interdependence between them. Moreover, since 2020 the Covid-19 pandemic has had a huge impact on the world economy. It is probably the deepest crisis since the end of World War II [31]. Therefore, it is worth using the DCC framework to model the dynamic correlation between emerging markets and the developed market in Europe during the Covid-19 pandemic.

3. Methods

In this section, we briefly present the dynamic conditional correlation model and multivariate distribution function known as copulas.

3.1. Dynamic conditional correlation model

In his seminal paper, Engle [18] introduced the autoregressive conditional heteroskedasticity (ARCH) model. Many extensions of this model have been proposed in the literature, including Bollerslev [10, 11], Engle and Ng [20], Glosten et al. [24] and Zakoian [32]. Models that describe the co-movement of financial returns are a natural extension of these univariate models, which former are used in risk management and portfolio allocation. A survey of multivariate GARCH models can be found in Bauwens et al. [8] and Silvennoinen and Teräsvirta [28]. In his paper, Bollerslev [11] introduced the first multivariate GARCH model which combines univariate ones with a constant conditional correlation matrix (the time-varying covariance matrix is decomposed into time-varying standard deviations and constant correlations). An extension of this model, the dynamic conditional correlation model, which allows conditional correlations to change in time, was introduced by Engle [19]. Both these models assume multivariate normality.

In its most popular version, the model DCC(1, 1) for bivariate data can be summarised by:

$$\begin{aligned} y_t &= \mu_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, H_t) \\ H_t &= D_t R_t D_t \\ D_t &= \mathrm{diag}(\sqrt{h_{1t}}, \sqrt{h_{2t}}) \\ R_t &= \mathrm{diag}(Q_t)^{-1/2} Q_t \mathrm{diag}(Q_t)^{-1/2} \\ Q_t &= (1-a-b)\bar{Q} + a z_{t-1} z'_{t-1} + b Q_{t-1} \end{aligned} \tag{1}$$

where $\bar{Q}$ is the unconditional covariance matrix of the standardised residuals $z_t = D_t^{-1}\varepsilon_t$ and μ_t is the conditional mean model. The matrices H_t, Q_t are the conditional covariance matrices of ε_t and z_t, respectively, whereas R_t is a conditional correlation matrix. The symbols h_{1t} and h_{2t} refer to conditional variances of the components of ε_t. The parameters a and b are restricted to be non-negative and their sum should be less than one. Cappiello et al. [12] introduced the asymmetric DCC model, in which negative shocks and positive shocks have a different impact on future correlations. Equation (1) changes to

$$Q_t = (1-a-b)\bar{Q} - gQ^- + a z_{t-1} {z'}_{t-1} + g z_t^- {z'}_t^- + b Q_{t-1} \tag{2}$$

where

$$z_t^- = \begin{cases} z_t, & z_t < 0 \\ 0, & z_t \geq 0 \end{cases}$$

and Q^- are the unconditional covariance matrix of z_t^-. The asymmetry parameter g should be nonnegative.

The conditional variances in the above set of equations are modelled with nonlinear asymmetric GARCH [20]. In comparison to the standard GARCH model, this model takes the leverage effect into account – negative returns have a greater impact on future volatility than positive ones.

3.2. Copulas

Sklar [29] introduced a new class of multivariate cumulative distribution functions, which are multivariate cumulative distributions with uniform margins. Assume that random variables X_1 and X_2 have continuous distribution functions F_1 and F_2 and joint distribution F. Sklar's theorem (see [27]) states that there exists function C (called the copula), such that $F(x_1, x_2) = C(u_1, u_2)$ with $u_1 = F_1(x_1)$ and $u_2 = F_2(x_2)$. From this, we see that the copula is a function that combines one-dimensional distributions into a multivariate distribution and then the equation holds

$$C(u_1, u_2) = F(F_1^{-1}(u_1), F_2^{-1}(u_2)) \tag{3}$$

The density of copulas is the mixed second derivative and can be expressed as

$$c(u, v) = \frac{f(F_1^{-1}(u_1), F_2^{-1}(u_2))}{f_1(F_1^{-1}(u_1))f_2(F_2^{-1}(u_2))} \tag{4}$$

f_1, f_2 and f are densities of F_1, F_2 and F, respectively. One of the best-known classes of copulas are elliptical copulas, that is, normal (Gaussian) and t. The first of them is expressed as

$$\begin{aligned} C_\rho^{\mathrm{Ga}}(u_1, u_2) &= \Phi_\rho(\Phi^{-1}(u_1), \Phi^{-1}(u_2)) \\ &= \int\limits_{-\infty}^{\Phi^{-1}(u_1)} \int\limits_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi(1-\rho^2)^{-1/2}} \exp\left(\frac{-(s_1^2 - 2\rho s_1 s_2 + s_2^2)}{2(1-\rho^2)}\right) ds_1 ds_2 \end{aligned} \tag{5}$$

where Φ_ρ is the cumulative distribution function of the bivariate standard normal with correlation coefficient ρ, while ϕ^{-1} is the inverse of the univariate cumulative distribution function of the standard normal.

The density of the copula (5) is given by

$$c_\rho^{\mathrm{Ga}}(u_1, u_2) = \frac{1}{(1-\rho^2)^{1/2}} \exp\left(\frac{\eta_1^2 + \eta_2^2}{2} + \frac{-(\eta_1^2 - 2\rho\eta_1\eta_2 + \eta_2^2)}{2(1-\rho^2)}\right) \tag{6}$$

where $\eta_1 = \Phi^{-1}(u_1)$ and $\eta_2 = \Phi^{-1}(u_2)$.

The t copula is based on the t distribution function and is given by

$$\begin{aligned} C_\rho^t(u_1, u_2) &= t_{\nu,\rho}(t_\nu^{-1}(u_1), t_\nu^{-1}(u_2)) \\ &= \int\limits_{-\infty}^{t_\nu^{-1}(u_1)} \int\limits_{-\infty}^{t_\nu^{-1}(u_2)} \frac{1}{2\pi(1-\rho^2)^{-1/2}} \left(1 + \frac{s_1^2 - 2\rho s_1 s_2 + s_2^2}{\nu(1-\rho^2)}\right)^{-(\nu+2)/2} ds_1 ds_2 \end{aligned} \tag{7}$$

where $t_{\nu,\rho}$ is the cumulative distribution function of the bivariate t cumulative distribution function with correlation coefficient ρ and ν degrees of freedom, whereas t_ν^{-1} is the inverse of the univariate cumulative distribution function of t with ν degrees of freedom. The density of copula (7) has the form

$$c_\rho^t(u_1,u_2) = (1-\rho^2)^{-1/2} \frac{\Gamma\left(\frac{\nu+2}{2}\right)\Gamma\left(\frac{\nu+2}{2}\right)}{\Gamma\left(\frac{\nu+2}{2}\right)^2} \frac{\left(1+\frac{\eta_1^2-2\rho\eta_1\eta_2+\eta_2^2}{\nu(1-\rho)^2}\right)^{-(\nu+2)/2}}{\prod_{j=1}^2\left(1+\frac{\eta_j^2}{\nu}\right)^{-(\nu+2)/2}} \tag{8}$$

where $\eta_1 = t_\nu^{-1}(u_1)$, $\eta_2 = t_\nu^{-1}(u_2)$ and Γ is Euler's gamma function.

To summarise, we use the (asymmetric) Dynamic Conditional Correlation model, where conditional variances are modelled with the NAGARCH(1,1) model, in which conditional marginal distributions are skew t-distribution of Fernandez and Steel [22]. Instead of the bivariate standard normal, we use the copula with constant parameter ν (or Gaussian if this parameter is insignificant).

4. Empirical results and discussion

This section contains the results of the estimation of the model presented in subsection 3.1. We consider the daily closing prices of six European indexes, namely, ATX, BUX, CAC, DAX, FTSE and WIG in the period from January 5, 2016, to June 1, 2022. We calculate the logarithmic returns (multiplied by 100) and basic summary statistics, which are presented in Table 1.

Table 1. Summary statistics of logarithmic returns

Index	Mean	St.dev.	Kurtosis	skewness
ATX	0.0158	1.4055	18.777	−1.2624
BUX	0.0391	1.3027	16.6491	−1.4877
CAC	0.0203	1.2369	17.3181	−1.0919
DAX	0.0186	1.2588	16.5682	−0.7273
FTSE	0.0128	1.0971	16.376	−0.9394
WIG	0.0063	1.2108	20.0161	−1.4482

We observe high kurtosis and negative skewness for every time series. When testing the normality (the Jarque-Bera test) we reject null in all cases. The results of the Ljung-Box test for autocorrelation give failing to reject the null (at a significance level of 10%) only for the WIG index.

In the first step, we filter the series with Vector autoregression models. The filtered series are modelled with the dynamic model. We pay attention to models with significant parameters (at a level of at least 10%). In this way, the asymmetry parameter can be excluded and the t copula replaced with the Gaussian one. The lack of value of parameter g indicates that the asymmetric DCC model has been replaced with a symmetric one (an example is the pair ATX–CAC). On the other hand, the lack of value of the parameter means that the t-copula was fitted worse than the Gaussian copula (according to SBC criterion or/and p-value ν, FTSE–WIG is an example of this). The lack of both means that the estimated model was symmetric DCC with the Gaussian copula. Table 2 contains the results of the estimation (the correlation parameter ρ in copulas (5) and (7) is conditional and changes in time)[1].

In most cases, the t-copula outperforms the normal copula with the significant asymmetry parameter in its dynamics according to Schwarz Bayesian criterion (SBC).

[1]More detailed results are available upon request.

Table 2. Estimation results (whole sample)

Pair of indexes	a	b	g	ν
ATX–BUX	0.0131	0.9248	0.045	12.2905
ATX–CAC	0.0294	0.9362	–	9.8848
ATX–DAX	0.0246	0.8916	0.0553	15.3642
ATX–FTSE	0.0388	0.8228	0.0917	12.3013
ATX–WIG	0.0113	0.9625	–	11.1063
BUX–CAC	0.0206	0.9292	0.0346	18.602
BUX–DAX	0.0259	0.9203	0.0261	17.8588
BUX–FTSE	0.0197	0.9562	–	13.1428
BUX–WIG	0.0177	0.9485	–	12.1995
CAC–DAX	0.0727	0.8679	0.0507	6.9302
CAC–FTSE	0.0353	0.9058	0.0675	16.0299
CAC–WIG	0.04	0.8993	–	20.5015
DAX–FTSE	0.0282	0.9259	0.055	15.7214
DAX–WIG	0.0318	0.9152	–	10.034
FTSE–WIG	0.0241	0.8888	0.0446	–

In Figure 1, we present an example of conditional variances (these series are very similar, regardless of which pair of indices they are associated with when modelling the pairs of series).

In March 2020, we observe a growth in conditional variance for every index. The maximum values are reached on 19 March 2020 (ATX, CAC, DAX, FTSE) and 13 March 2020 (BUX and WIG, for BUX this is the second highest value, and the first is on 2 March 2022). This is the case for all variances, regardless of the pair of indices under consideration. These dates are significant. For example on 19 March 2020 California (the most important state in the US) became the first state to issue a stay-at-home order, mandating all residents to stay at home except to go to an essential job or a shop for essential needs. The order also instructed healthcare systems to prioritise services for those who are the sickest. On the other hand, on 13 March 2020 the head of the World Health Organization announced that Europe had become the centre of the Covid-19 pandemic. In Figure 2 we present conditional correlations.

Again we observe an increase in the level of correlation from the announcement of the global pandemic (on 30 December 2019) with the highest value (the second highest in the case pair CAC-WIG) on 13 March 2020. Thereafter, the level of correlations declines until mid-2021. To identify the time of increased risk on the stock markets we apply Bai and Perron's procedure [4, 5] to the average level of the logarithm of the estimated conditional variances. The optimal partition based on the minimisation of the SBC has 6 segments (5 breakpoints). We are interested in the date nearest to the beginning of the pandemic. This procedure identifies a structural break in the second half of February 2020. If we test for one breakpoint, this is found on 24 February 2020. The same procedure is applied to conditional correlations. In this case, the structural change occurs in January and February 2020 in 10 out of 15 cases, (especially in the second half of these months).

We split our samples into two subsamples. We choose 30 December 2019 as the split date and estimate our dynamic model once again in both subsamples. The results are presented in Table 3.

The results are mixed. There is no dominant model, but we can observe that during the Covid period, the sum of estimated parameters of the DCC (a and b) model is greater than in the pre-Covid period. This leads one to the conclusion that dependence on conditional covariances between consecutive days (from $t-1$ to t) increases. Given the estimated conditional correlations in the subsamples, we calculate their

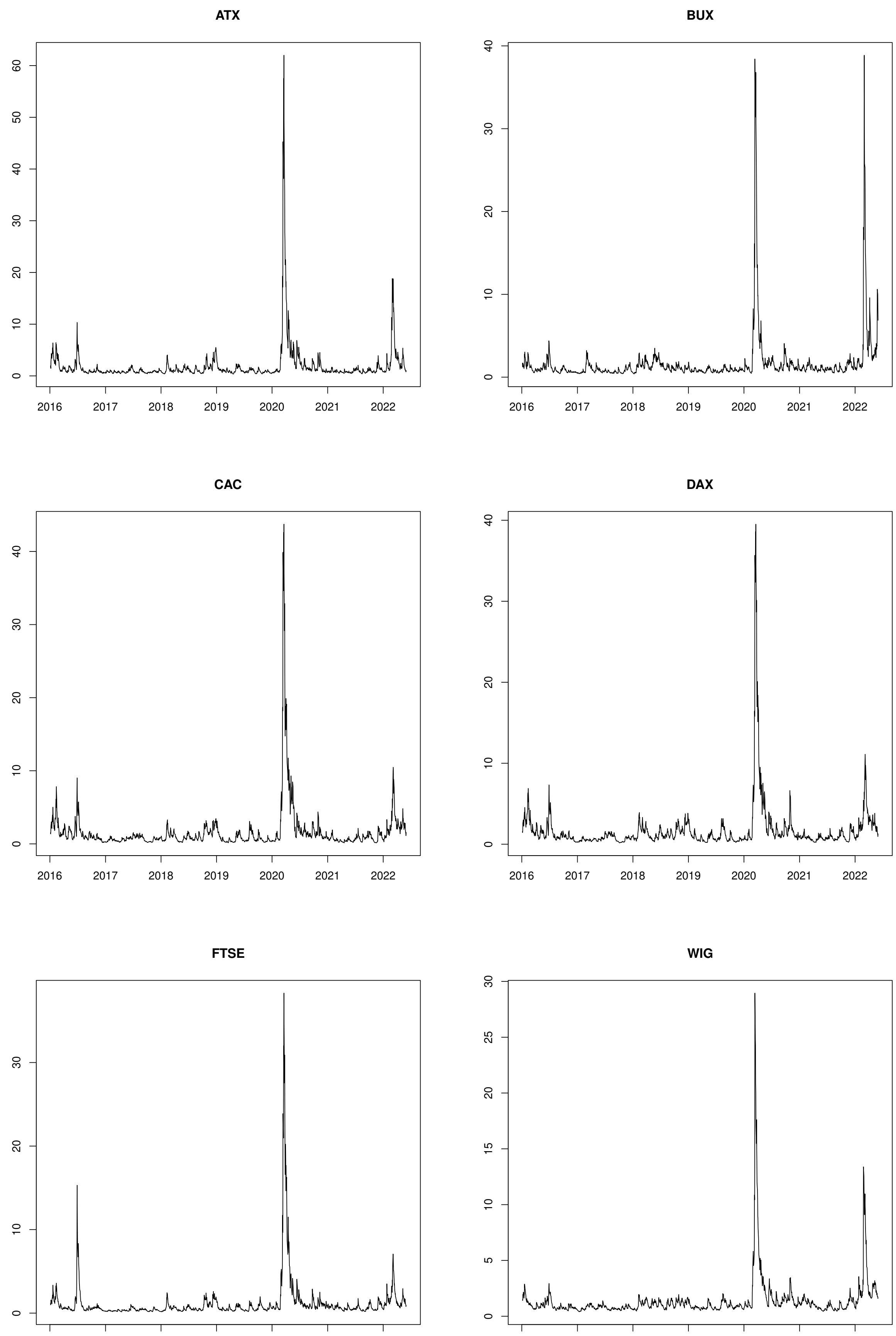

Figure 1. Conditional variances from the dynamic model

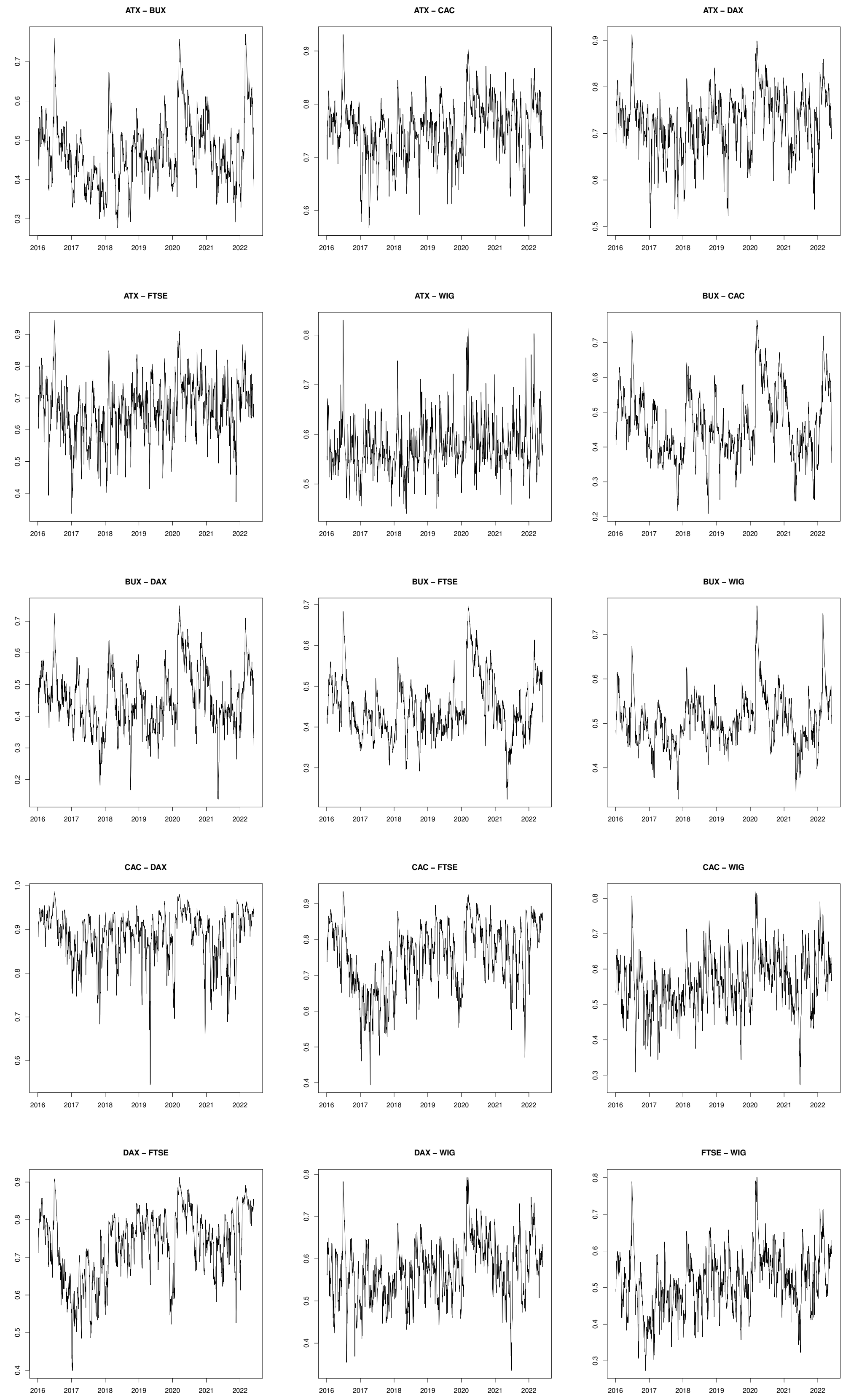

Figure 2. Conditional correlation from DCC-copula model

Table 3. Estimation results in subsamples

Pair of indexes	Pre-Covid period				Covid period			
	a	b	g	ν	a	b	g	ν
ATX–BUX	0.0089	0.9241	–	9.8419	0.0176	0.9109	0.0728	–
ATX–CAC	0.0181	0.7786	0.1125	16.7816	0.0212	0.9616	–	8.3432
ATX–DAX	0.0254	0.7885	0.0877	9.0809	0.0377	0.933	–	–
ATX–FTSE	0.0351	0.7317	0.1849	13.3505	0.0349	0.9295	–	16.4327
ATX–WIG	0.0366	0.7498	–	13.8682	0.0048	0.9781	–	9.8466
BUX–CAC	0.0189	0.9323	–	–	0.0356	0.9401	–	–
BUX–DAX	0.027	0.9218	–	–	0.0434	0.9129	–	9.8167
BUX–FTSE	0.0107	0.8777	–	–	0.0253	0.9561	–	8.0194
BUX–WIG	0.0216	0.883	–	12.689	0.0184	0.9515	–	–
CAC–DAX	0.0715	0.8621	–	6.5778	0.0746	0.8413	0.0922	7.6129
CAC–FTSE	0.0491	0.8689	0.068	–	0.0316	0.9582	–	9.4763
CAC–WIG	0.0444	0.7296	–	–	0.0335	0.9272	–	–
DAX–FTSE	0.0347	0.8898	0.058	–	0.0195	0.9539	0.0454	8.1515
DAX–WIG	0.0137	0.8548	–	11.0177	0.0471	0.8926	–	–
FTSE–WIG	0.0156	0.8334	0.0675	–	0.0274	0.9219	–	–

Table 4. Sorted mean values of correlations

Pre-Covid period	Covid period
BUX–FTSE	BUX–FTSE
BUX–DAX	BUX–DAX
BUX–CAC	BUX–CAC
ATX–BUX	BUX–WIG
BUX–WIG	ATX–BUX
FTSE–WIG	FTSE–WIG
CAC–WIG	CAC–WIG
ATX–WIG	ATX–WIG
DAX–WIG	DAX–WIG
ATX–FTSE	ATX–FTSE
DAX–FTSE	ATX–DAX
ATX–DAX	ATX–CAC
ATX–CAC	DAX–FTSE
CAC–FTSE	CAC–FTSE
CAC–DAX	CAC–DAX

means and apply a simple statistical test of their equality. For all pairs, the mean value of the conditional correlations in the pre-Covid period was statistically lower than in the Covid period, which supports the conjecture about contagion in the time period after the outbreak of the Covid-19 pandemic. Additionally, we compare the mean values of correlations in the subperiods between all pairs of indexes. Table 4 presents a ranking of the pairs according to their mean values (in ascending order).

In 10 out of 15 cases the sorted pairs are in the same place. We observe the weakest dependence for pairs made up of the BUX and WIG indexes. On the other hand, the strongest consist of CAC, DAX and FTSE.

5. Conclusions

This study examines the influence of the pandemic on selected European stock returns. The use of a model with a time-varying correlation and flexible distribution (copula) allows dynamic dependence to be described. We see an increase in risk (volatility) from the announcement of the global pandemic (on 30 December 2019), with its highest values on 13 March 2020 and 19 March 2020. The first date is especially significant. On this day the head of the World Health Organization announced that Europe had become the centre of the Covid-19 pandemic. This also holds true for conditional correlations. The dependences between stock returns rapidly increased but then declined. We also used the procedure of searching for breakpoints both in volatilities and correlations, especially at times closer to the beginning of the pandemic.

The procedure identifies a structural break in the second half of February 2020. Splitting our samples into two subsamples (using 30 December 2019 as a split date) allowed us to test for a contagion effect. For all pairs, the mean value of the conditional correlations in the pre-Covid period was statistically lower than in the Covid period, which is a sign of contagion. The ranking of the most dependent indexes is fairly stable. We observe the weakest dependence for pairs made up of indexes from emerging markets and the strongest dependence for developed ones. A study of the relationship between sectors of different economies will be the subject of future research.

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