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The dependencies of subindexes of Stoxx 600 during the Covid-19 pandemic

1. Introduction

The Covid-19 outbreak has been the source of a huge rise in volatility, which has been reflected in financial market turbulence. The values of the distribution of asset returns have increased, intailing a growing risk to financial markets. In addition, the extreme values occur almost simultaneously across asset classes and countries. The rising correlations diminish the positive effects of diversification and finally make financial markets over the world systemically less stable.

A knowledge of the return distribution and risk profiles of stock prices supports channels for profit optimization. Detecting informational inefficiency on financial markets is an important research direction from the point of view of profit maximalization. Stock indexes and subindexes represent an entire stock exchange and particular sectors are used frequently to test for market efficiency.

Most studies on the relationship between indexes use indexes across countries. However, dependencies between subindexes across countries and subindexes and indexes are not frequent topics in the financial literature.

The analysis of the behavior and interrelations between subindexes during the pandemic period will be useful in determining changes in the roles of the major sectors and subsectors of the economy during a time of crisis. This knowledge may be interesting for both individual and institutional investors and may also be

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useful with respect to the potential diversification of their internationally based portfolios as an investment. The lack of a correlation, or only a small correlation, between these subindexes is a very desired property. The consequence is risk reduction arising from portfolio diversification based on these indexed assets.

This empirical study has three aims. Firstly, it aims to find the similarities and dissimilarities in the behavior of subindexes around the beginning of the Covid-19 pandemic. The next topic is the level of dependencies between the subindexes in the time period under consideration. The third aim is to determine the usefulness of the ΔCoVar and MES methodology in this research.

In the next section we provide an overview of selected studies on dependences between subindexes. We use the methodology ΔCoVar, MES and DCC-copulas to assess the relationships between the stock indexes and subindexes under investigation.

2. Literature review

The first papers about the dependence between stock market indexes were published in the 1980's (Higgins, 1988). The authors established whether interrelations are an important source important with respect to forecasting the future level of both stock prices and economic growth of countries. They tried to convince readers that the lack of a weak form of market efficiency is induced by the high level of correlation between the main sector indexes (Arbelaez et al., 2001). Investigations into this problem were begun by Just in 1996 (compare Ratner, 1996). In order to establish the market efficiency of the Madrid Stock Exchange, the author applied nine major indexes from this stock exchange. He detected that the distribution of index returns was non-normal and did not support the random walk hypothesis. In the study by H. Arbeláez et al. (2001), mentioned above, the short-term and long-term interrelations between some stock indexes of the Medellin Stock Exchange (now the Colombia Stock Exchange) are shown. In their comprehensive study, the authors employed a number of procedures and tests of stationarity, including causality, cointegration, impulse response function and variance decomposition and a VEC model based on daily prices over 7 years. They confirmed the existence of a significant interrelation between these indexes.

In the first years of the twenty-first century, some papers on the Athens Stock Exchange (ASE) were published. In their studies M.G. Kavussanos and E. Dockery (2001) came to the conclusion that the Athens Stock Exchange is not efficient in a semi-strong sense.

G.D. Siourounis (2002) used GARCH type models and applied them to the data from the ASE Market. The returns were correlated and their volatility showed autocorrelation. According to Siourinis, the ASE is not weakly efficient. Niarchos and Alexakis (2003) also detected particular price patterns. Due to these patterns, investors can achieve abnormal returns so the ASE is inefficient. Panagiotidis (2005) detected that after the introduction of the Euro the random walk hypothesis was not valid for three different FTSE/ASE indexes.

In a study by T. Patra and S.S. Poshakwale (2008) the subject of research was six sectors of the Athens Stock Exchange: Banking, Industrial, Construction, Insurance, Investment and Holding. These sectors constitute more than 63% of the ASE capitalization. The authors found that the sector indexes are not strongly interrelated in the long term. They found that in the short term the banking sector impacted on the returns and volatility of other sectors. The source of the variance of the returns for most subindexes is their own innovations. The most important banking sector contributed 25% of variance in the construction sector and the insurance sector was responsible for 15% of the variance in the industrial, investment and holding sectors. So, the predominant role was played by the banking sector. Therefore, one can assume that the banking sector may allow at least a short-term prediction of changes in the other sector indexes. The general conclusion is that the ASE did not fulfill the assumptions deriving from the weak efficiency of the market.

The transfer of information between stock markets and regions has also become a popular topic in contributions by many well-known scholars outside Europe and North America. These contributions have also focused on the economies of South Asia and Latin America.

After the global crises of 2008, the imbalances in the global financial and economic system, including emerging markets in different parts of the world, became clear. Besides South Asia and Latin America investors have paid attention to the particular markets of the Middle East and North Africa (Lagoarde-Segot, Lucey, 2008). They are characterized by relatively high returns and volatility, weak interrelations with the largest world markets, and volatility clustering. One of the main aims of T. Lagoarde-Segot and B. Lucey's paper was to detect the level of correlation and the channels of information flow across sectors in these regions. The authors tried to assess the relative importance of the sectors under consideration in their explanation of the variations in returns in these sectors. The second task was to determine information channels across sectors within a stock market (Wang et al., 2005).

In the new situation that has arisen following the outbreak of the Covid-19 pandemic in 2020 and the introduction of many sanitary restrictions in some sectors, the interrelations between indexes and subindexes on an international level are of even greater interest, particularly for policy makers. In our analysis of the linkages between the subindexes of Stoxx Europe 600 index, a methodology known as ΔCoVar is used. This measure of systemic risk was developed by T. Adrian and M.K. Brunnermeier (2011) in order to identify or rank systemically important financial institutions. A recent contribution based on this measure is by M.L. Bianchi and A.M. Sorrentino (2020), who estimate systemic risk for Italian and main European banks. For this purpose, the authors employed the quantile regression and a non-parametric method. G. Girardi and A.T. Ergün (2013) present the results of an estimation of the systemic risk contributions (based on the multivariate GARCH model) of four financial industry groups, including a large number of institutions.

Q. Xu et al. (2018) assess systemic risk in the Chinese banking sector by applying the DCC-MIDAS model with Student's *t* distribution. The multivariate distributions known as copulas (Sklar, 1959) are a useful tool in dependence modeling and risk estimation employed by, among others – Guloksuz and Kumar, 2020; Fabozzi et al. 2013, and Gong et al. 2014.

For dependence evaluation, D.H. Oh and A.J. Patton (2018) suggested a new class of copula-based dynamic models. The factor copulas employed by H. Manner et al. (2021) are considered a tool for modeling high dimensional conditional distributions, helping the estimation of various indicators of systemic risk. This model was applied to a collection of daily CDS (credit default swap) spreads on 100 U.S. firms.

The remainder of this paper is structured as follows. The next section outlines the methodology employed, while the following section describes the dataset and empirical results. The final part of the paper presents some conclusions.

3. Methodology

In this section we briefly quote the dynamic model and systemic risk measures employed in this paper.

3.1. Asymmetric dynamic conditional correlation model

In the literature one can find many models that allow the dependence between time series to be described. The multivariate GARCH belongs to a class of models that allow one to predict second-order moments of returns (see Bauwens et al., 2006 for survey). One of the most popular models in this class is Engle's Dynamic Conditional Correlation (2002), which enables the time varying covariance matrix to be decomposed into standard deviations and a time-varying correlation matrix.

Particular attention has been given to whether changes in the correlation between international asset markets demonstrate evidence of an asymmetric response to negative returns. Taking this into account, L. Cappiello et al. (2006) generalized Engle's to asymmetric cases. We adopt this model along with the bivariate *t* copula, which allows one to describe the tail dependence of the financial time series.

3.2. Systemic risk measurement with ΔCoVar and MES

In this paper we consider two commonly used systemic risks. The first of them is ΔCoVar, which is based on the concept of Value at Risk (Adrian and Brunnermeier, 2011, 2016). Let $\mathbb{C}(r_{st})$ be some event for returns of subindex *s*. Then ΔCoVar at confidence level α corresponds to the conditional Value at Risk of the market return r_{mt} (main stock index)

$$P\left(r_{mt} \leq CoVaR_t^{m|\mathbb{C}(r_{st})} | \mathbb{C}(r_{st})\right) = \alpha \tag{1}$$

We consider event $\mathbb{C}(r_{st})$ equal to the Value at Risk of the subindex return at the same level α. The difference between the CoVar at level alpha and CoVar computed in median state is denoted as ΔCoVar (Benoit et al., 2013)

$$\Delta CoVaR_{st}(\alpha) = CoVaR_t^{m|r_{st}=VaR_{st}(\alpha)} - CoVaR_t^{m|r_{st}=Median(r_{st})} \tag{2}$$

where $VaR_{st}(\alpha)$ satisfies

$$P\left(r_{st} \langle VaR_{st}(\alpha) \middle| \mathcal{F}_{t-1}\right) = \alpha \tag{3}$$

where $\mathcal{F}_{t-1}$ is information available up to time $t-1$. $\Delta CoVaR_{st}$ denotes the part of the risk of the market that can be attributed to a given sector.

The second measure that we consider is based on the concept of Expected Shortfall and is defined in (Acharya et al. 2010). The Marginal Expected Shortfall computed at time *t* (given the information up to time $t-1$) is defined as

$$MES_{st}(C) = E_{t-1}(r_{st} \mid r_{mt} < C) \tag{4}$$

where the threshold *C* defines the distress event. MES measures the increase in the risk of the market (expressed by Expected Shortfall of market returns), which is induced by a marginal increase in the weight of sector.

In the literature one can find many methods of computing ΔCoVar and MES. We calculate these measures on the basis of the model by Brownless and Engle (2012)

DCC but replace the bivariate normal distribution with dynamic bivariate t-copula. It can be shown that (see Benoit et al., 2019) ΔCoVar can be expressed as

$$\Delta \text{CoVaR}_{st}(\alpha) = \gamma_{st}\left[VaR_{st}(\alpha) - VaR_{st}(0.5)\right] \tag{5}$$

with $\gamma_{st} = \rho_{st}\sqrt{h_{mt}} / \sqrt{h_{st}}$, where ρ_{st} is a conditional correlation coefficient at time t between market and subindex returns.

During the computation of MES we set the distress event to Value at Risk of the market return $VaR_{mt}(\alpha)$. S. Benoit et al. (2013) showed that in these settings

$$MES_{st}(\alpha) = \beta_{st} ES_{mt}(\alpha) \tag{6}$$

where $\beta_{st} = \rho_{st}\sqrt{h_{st}} / \sqrt{h_{mt}}$, is time-varying conditional β and $E_{mt}(\alpha) = E_{t-1}(r_{mt} \mid r_{mt} < VaR_{mt}(\alpha))$ is the expected shortfall of the market. From this, one can conclude that considering the MES of a sector is the same as considering the beta of a subindex.

Thus, MES measures how the financial institution contributes to the overall risk of the financial system. To summarize, MES takes the returns of a sector into account when the market is in left tail of the return distribution, and ΔCoVar looks at the market when the sector falls in the left tail of the return distribution. The sectors with the highest MES are the greatest drivers of systemic risk (they contribute the most to the decline of the market). The sectors with the highest ΔCoVar make the greatest contribution to market risk. In our approach we consider the absolute values of these measures. Both measures can lead to different conclusions when identifying the least risky and the riskiest sectors. S. Benoit et al. (2013) derived conditions under which rankings based on both measures are convergent. In the empirical part of this paper, we consider the dependence of sectors as well and measure the part of the risk of a given sector that can be attributed to another sector.

4. The data

We consider the daily closing prices of the Stoxx Europe 600 index along with their sectoral indexes in the period 03.01.2018 to 16.04.2021. In Table 1 we present the descriptive statistics of logarithmic returns (in percentages), along with the results of Jarque-Bera and Ljung-Box testing (p-values are reported).

Both the STOXX 600 index and all subindexes are non-normally distributed. The time series of returns are characterized by high kurtosis and negative skewness (in all cases we reject the null of normality). With one exception (Health Care) we also reject the null of lack of autocorrelation (Ljung-Box test).

Table 1

Summary statistics of logarithmic returns

(Sub)index	Mean	S.D.	Kurtosis	Skewness	L-B	J-B
STOXX 600	0.02	1.16	23.56	–1.74	0.00	0.00
Automobiles & Parts	0.01	1.91	17.36	–0.66	0.00	0.00
Banks	–0.04	1.82	14.55	–0.63	0.00	0.00
Basic Resources	0.03	1.89	14.07	–0.44	0.00	0.00
Chemicals	0.03	1.28	10.71	–0.88	0.00	0.00
Construction Materials	0.03	1.49	20.00	–1.47	0.00	0.00
Financial Services	0.04	1.40	22.35	–1.10	0.00	0.00
Food & Beverage	0.01	1.03	14.47	–1.23	0.00	0.00
Health Care	0.03	1.04	12.55	–0.95	0.24	0.00
Industrial Goods Services	0.04	1.42	15.84	–1.04	0.00	0.00
Insurance	0.01	1.57	29.14	–0.97	0.00	0.00
Media	0.02	1.27	16.78	–0.90	0.00	0.00
Oil & Gas	–0.03	1.87	25.42	–1.17	0.00	0.00
Personal Goods	0.02	1.13	11.95	–1.07	0.00	0.00
Real Estate Price	0.00	1.25	22.34	–1.57	0.00	0.00
Retail	0.04	1.20	12.64	–0.86	0.00	0.00
Technology	0.06	1.51	9.89	–0.87	0.00	0.00
Telecommunications	–0.03	1.21	21.73	–0.99	0.00	0.00
Travel & Leisure	0.00	1.82	13.65	–0.37	0.00	0.00
Utilities	0.04	1.25	33.48	–2.58	0.00	0.00

5. Estimation results

In this section we present the results of the estimation of the model presented in subsection 3.1 and compute the dynamic measure of risk from subsection 3.2. In most cases we apply Engle and Ng’s Nonlinear Asymmetric GARCH model (1993) to model conditional variances. For the subsectors Insurance and Utilities, the parameter of rotation, at a level of 10%, is not significant. In this case we replace NAGARCH with a basic GARCH model. In Figure 1 we present the conditional variances of all subindexes along with the conditional variance of STOXX Europe 600 (from pair with Automobiles & Parts).

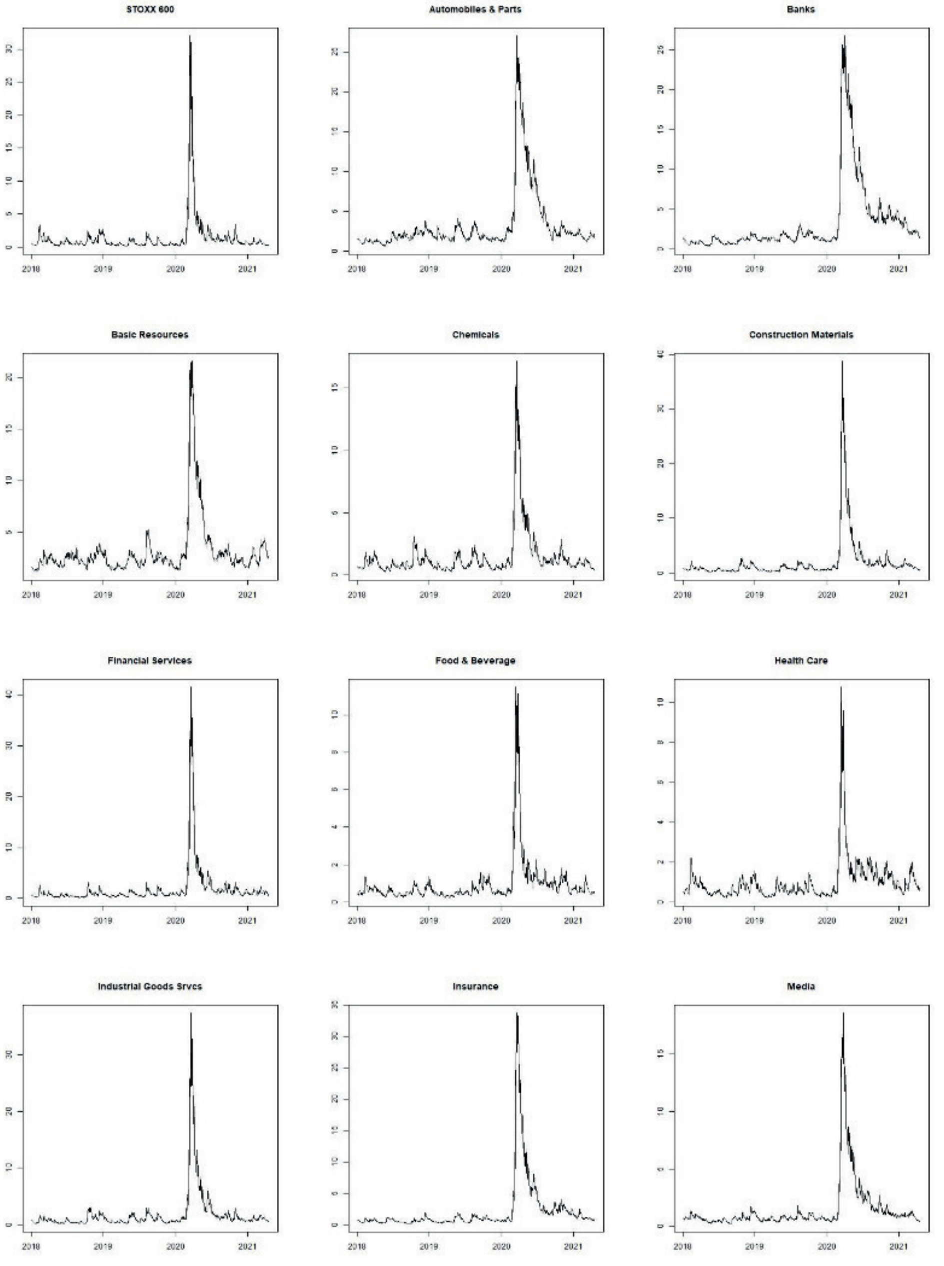

Figure 1. Conditional variances from DCC – copula model

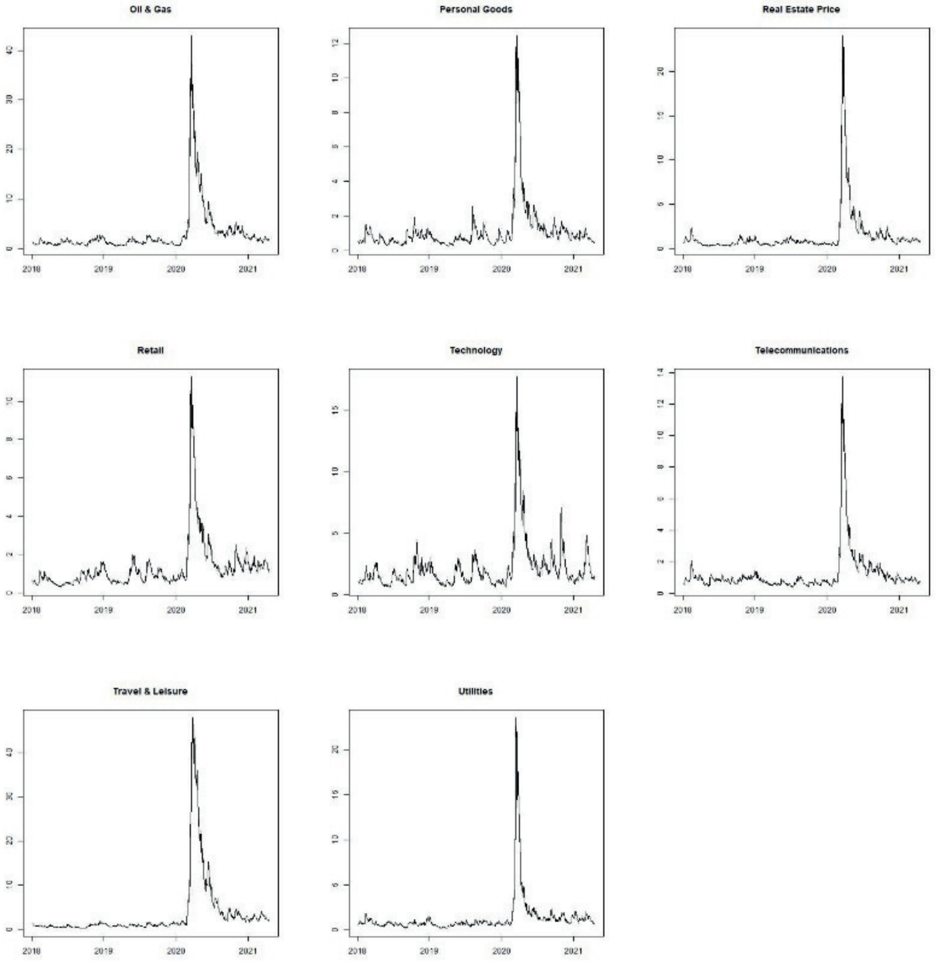

Figure 1. cont.

On the basis of dynamic models, we computed the conditional correlations. For four sectors (Food & Beverage, Health Care, Telecommunications and Travel & Leisure) the parameter of asymmetry, at a level of 10%, was not significant, and we used the standard DCC(1,1) model. Using conditional variances and correlations we compute systemic risk measures in which distress events are Value at Risk at a significance level of 5%. They are presented in Figure 2.

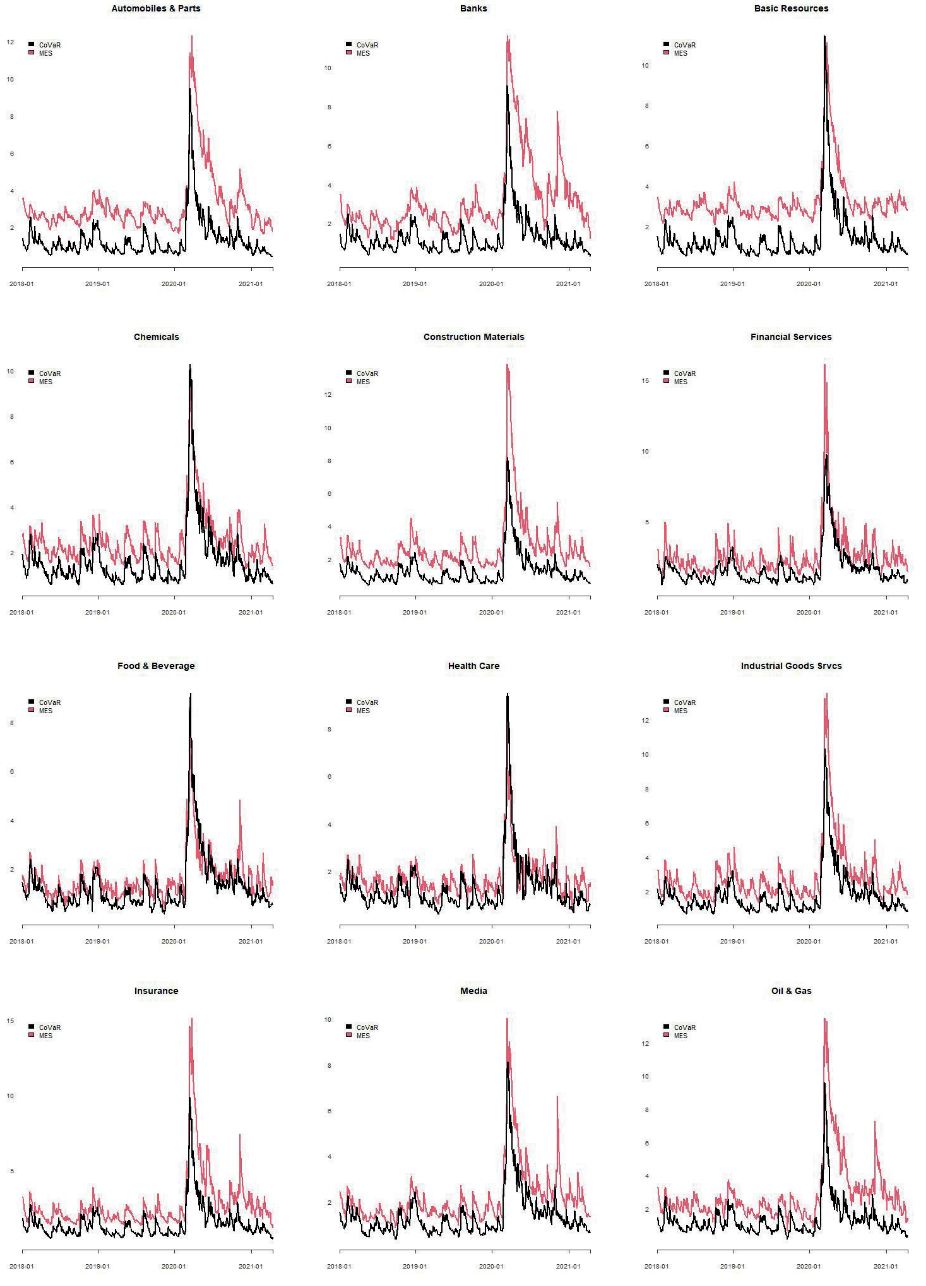

Figure 2. Systemic risk measures from dynamic model

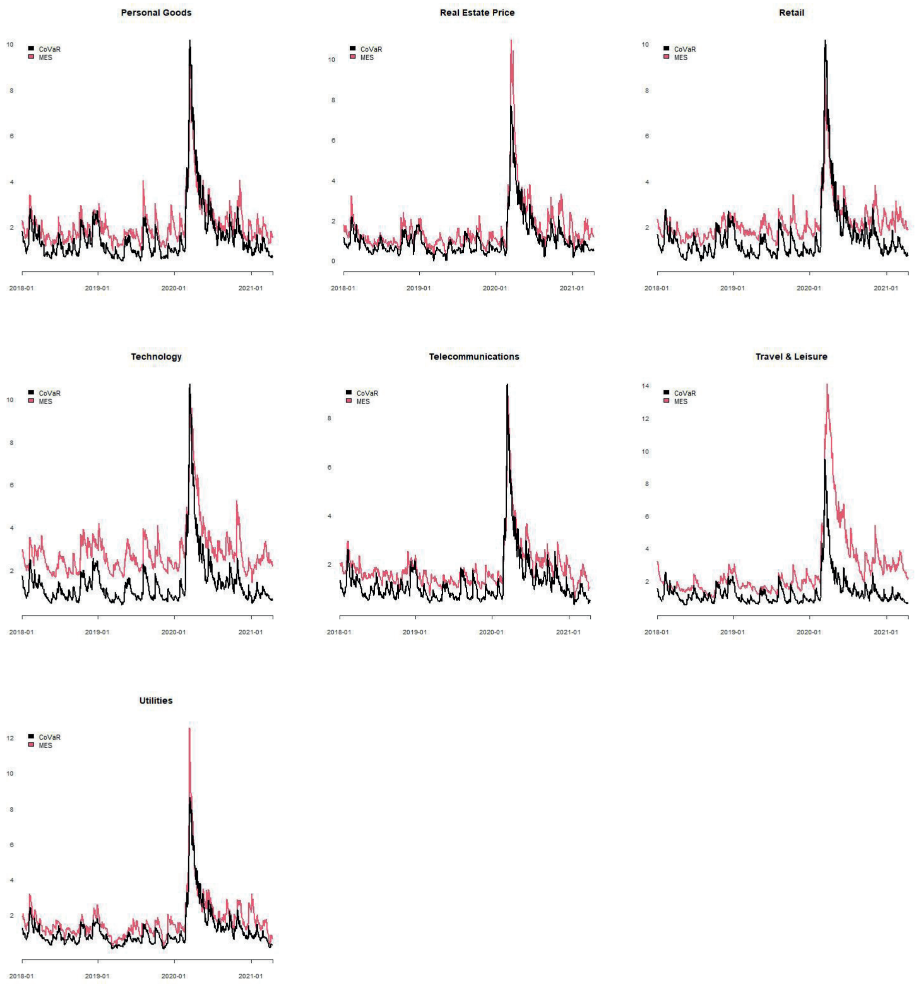

Figure 2. cont.

We observe that the plots of systemic risk measures are very similar and these time series are very strong correlated. The minimum value of Pearson and Spearman correlation coefficients is found for the Travel & Leisure subindex (0.7935) and Basic Resources (0.6367), respectively.

After sorting, we computed the daily percentage of concordant pairs between risk measures. This is illustrated in Figure 3.

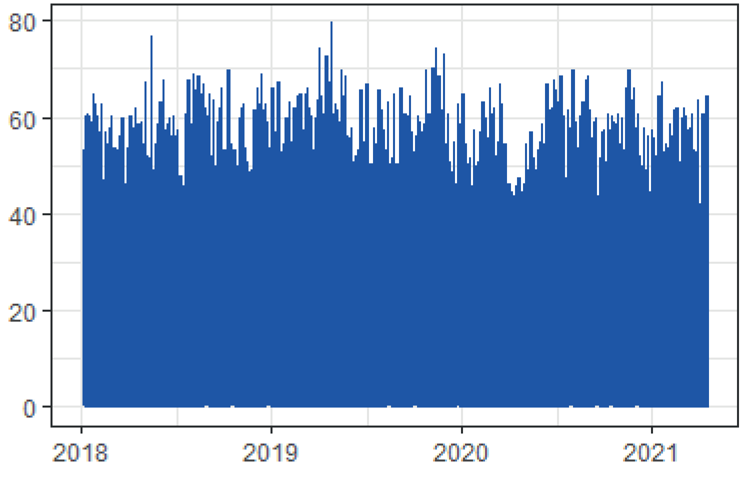

Figure 3. Percentage of concordant pairs between risk measures

On average, for all sectors, the percentage of such pairs is equal to 53.13%. When considering the three riskiest sectors we obtain a value of 51.58%.

To establish whether the rankings produced by systemic risk measures are stable, we computed the Kendall correlation coefficient between the systemic risk ranking obtained on consecutive days. When all 19 subsectors are taken into account, the mean values of correlation coefficient for ΔCoVar and MES are 0.36 and 0.47, respectively. When we consider the three riskiest sectors, we obtain the values 0.44 and 0.52, which indicates poor stability of rankings (the number of days with a perfect positive correlation is equal to 455 and 481, respectively).

It can also be seen that the maximum values of ΔCoVar and MES are noted in similar periods. This is the case for conditional variances as well. In Table 2 we present the dates on which the maximum values of conditional variances and systemic risk measures are observed.

Table 2

Dates of the maximum values of conditional variances and systemic risk measures

Subindex	Variance	ΔCoVar	MES
Automobiles & Parts	25.03.2020	17.03.2020	25.03.2020
Banks	17.03.2020	13.03.2020	17.03.2020
Basic Resources	25.03.2020	13.03.2020	25.03.2020

Table 2 cont.

Chemicals	13.03.2020	17.03.2020	13.03.2020
Construction Materials	17.03.2020	17.03.2020	13.03.2020
Financial Services	13.03.2020	24.03.2020	13.03.2020
Food & Beverage	13.03.2020	19.03.2020	13.03.2020
Health Care	13.03.2020	17.03.2020	13.03.2020
Industrial Goods Services	25.03.2020	17.03.2020	25.03.2020
Insurance	25.03.2020	13.03.2020	25.03.2020
Media	13.03.2020	17.03.2020	13.03.2020
Oil & Gas	25.03.2020	13.03.2020	13.03.2020
Personal Goods	13.03.2020	17.03.2020	13.03.2020
Real Estate Price	17.03.2020	13.03.2020	17.03.2020
Retail	13.03.2020	17.03.2020	13.03.2020
Technology	13.03.2020	17.03.2020	13.03.2020
Telecommunications	18.03.2020	17.03.2020	18.03.2020
Travel & Leisure	25.03.2020	13.03.2020	25.03.2020
Utilities	13.03.2020	17.03.2020	13.03.2020

The most frequent three dates are 13.03.2020, 17.03.2020, 25.03.2020 and it can be easily seen that they are not coincidental with the maximum values of the conditional correlations. Obviously, it is not easy to explain the rapid increase in risk. We noted that on 13 March 2020 the head of the World Health Organization announced that Europe was then the centre of the COVID-19 pandemic, and on 17 March 2020 the coronavirus threat risk in Germany was raised from moderate to high. We noted that the STOXX 600 Europe index decreased on 16 March, along with decreases in its subindexes, but on 17 March 2020 it mostly increased (similary to, for example, the DAX index). On both 24 and 25 March 2020 the STOXX 600 Europe index and subindexes increased (with returns of 8% and 3% of the main index on those days). Regarding the pandemic news, on 25 March 2020 Spain recorded more total deaths than any country except Italy. On 13 March 2020 the riskiest sectors were Basic Resources according to ΔCoVar and Financial Services according to MES, whereas the sectors with the lowest risk were Real Estate Price and Health Care. On 17 March 2020 the situation was analogous. On 25 March 2020 the most and least risky sectors were the same in terms of ΔCoVar, but for MES these sectors were Insurance and Food & Beverage. At the end of our sample, considering ΔCoVar Financial Services turned out the riskiest, whereas Utilities the least. According to MES the riskiest and least risky are Basic Resources and Utilities, respectively.

Wishing to construct rankings of sectors that are characterized by the highest and lowest mean values of systemic risk, we adopt Bai and Perron's test of multiple structural breaks (1998, 2003), in the time series of ΔCoVar and MES.

If $y_t = m_i + \varepsilon_t$ be the series of systemic risk under consideration with mean m_i and error term ε_t for $t = T_{i-1} + 1, T_{i-1} + 2, \ldots, T_i$ and $i = 1, 2, \ldots, M + 1$. The unknown break dates (or optimal partition) $T_1, T_2, \ldots, T_M$ and their number are found using methods of least squares and the Bayesian Information Criterion. Three breakpoints were found for some subindexes, but we only report the dates of breakpoints found during the pandemic period, which are presented in the Table 3.

Table 3

Dates of breakpoints in systemic risk measures

Subindex	ΔCoVar		MES	
Automobiles & Parts	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Banks	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Basic Resources	24.02.2020	20.08.2020	27.01.2020	23.07.2020
Chemicals	24.02.2020	20.08.2020	27.01.2020	23.07.2020
Construction Materials	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Financial Services	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Food & Beverage	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Health Care	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Industrial Goods Services	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Insurance	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Media	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Oil & Gas	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Personal Goods	24.02.2020	20.08.2020	20.02.2020	18.08.2020
Real Estate Price	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Retail	24.02.2020	20.08.2020	20.02.2020	18.08.2020
Technology	24.02.2020	20.08.2020	27.01.2020	23.07.2020
Telecommunications	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Travel & Leisure	24.02.2020	20.08.2020	24.02.2020	20.08.2020
Utilities	24.02.2020	20.08.2020	24.02.2020	20.08.2020

In the case of ΔCoVar breakpoints are found at the same time as on 24.02.2020 (on that day STOXX 600 Europe dropped 3.79% and, for example, DAX dropped about 4%) and 20.08.2020 (because of bad forecasts concerning the prognosis of the U.S. economy published by the Fed at its July FOMC Wall Street meeting, U.S. stock exchanges closed lower than before; additional factors with an impact on stock exchanges were problems and tensions between the United States and China, which reached their culmination on those days). For MES, these dates occur very often.

We divide our sample with these dates and compute the mean values of ΔCoVar and MES and in computing the mean daily values, we rank the sectors. The Tables 4 and 5 present these values in descending order.

Table 4

Ranked mean values of ΔCoVar in subperiods

from 04.01.2018 to 24.02.2020	**from 25.02.2020 to 20.08.2020**	**from 21.09.2020 to 16.04.2021**
Industrial Goods Services	Industrial Goods Services	Industrial Goods Services
Financial Services	Financial Services	Financial Services
Chemicals	Personal Goods	Personal Goods
Personal Goods	Chemicals	Retail
Retail	Retail	Chemicals
Insurance	Basic Resources	Media
Basic Resources	Technology	Insurance
Travel & Leisure	Insurance	Basic Resources
Oil & Gas	Food & Beverage	Food & Beverage
Technology	Media	Oil & Gas
Automobiles & Parts	Automobiles & Parts	Construction Materials
Banks	Utilities	Technology
Media	Health Care	Travel & Leisure
Construction Materials	Banks	Automobiles & Parts
Health Care	Telecommunications	Banks
Telecommunications	Construction Materials	Telecommunications
Food & Beverage	Oil & Gas	Health Care
Utilities	Travel & Leisure	Utilities
Real Estate Price	Real Estate Price	Real Estate Price

Table 5

Ranked mean values of MES in subperiods

from 04.01.2018 to 24.02.2020	**from 25.02.2020 to 20.08.2020**	**from 21.09.2020 to 16.04.2021**
Basic Resources	Travel & Leisure	Banks
Automobiles & Parts	Banks	Oil & Gas
Technology	Automobiles & Parts	Travel & Leisure
Banks	Oil & Gas	Basic Resources
Industrial Goods Services	Insurance	Insurance
Chemicals	Industrial Goods Services	Automobiles & Parts
Construction Materials	Construction Materials	Technology
Financial Services	Basic Resources	Construction Materials
Oil & Gas	Financial Services	Industrial Goods Services
Insurance	Technology	Financial Services
Retail	Media	Media
Personal Goods	Chemicals	Retail
Travel & Leisure	Personal Goods	Chemicals
Media	Utilities	Personal Goods
Telecommunications	Retail	Utilities
Health Care	Real Estate Price	Telecommunications
Food & Beverage	Telecommunications	Food & Beverage
Utilities	Food & Beverage	Health Care
Real Estate Price	Health Care	Real Estate Price

From Table 4 it can be seen that the sectors with the highest and lowest DCoVar are Industrial Goods Services and Real Estate Price, respectively, regardless of the periods. The rankings of MES are very different and there is no clear pattern. In the most critical period, the highest mean value of MES is assigned to the Travel & Leisure (18 place in ranking of ΔCoVar) sector and the lowest to the Health Care (13 place in ranking of ΔCoVar sector. We observe the similarity of rankings before and after this period (Real Estate Price at the bottom of the tables). Regarding the concordance of rankings according to the mean values of systemic risk we note 101 concordant pairs for the full sample (59% of all pairs), whereas for subperiods: 84 (49%), 70 (41%) and 79 (46%).

In Tables 6 and 7 we present the percentage changes of systemic risk measures with respect to the subperiod 04.01.2018 to 24.02.2020.

Table 6

Percentage changes of ΔCoVar

from 24.02.2020 to 20.08.2020		from 16.04.2020 to 16.04.2021	
Utilities	293.18	Utilities	31.46
Real Estate Price	258.38	Food & Beverage	30.99
Food & Beverage	256.13	Media	26.25
Basic Resources	216.95	Real Estate Price	22.83
Telecommunications	207.82	Insurance	15.02
Technology	206.15	Retail	13.39
Media	200.32	Personal Goods	12.66
Personal Goods	198.22	Financial Services	12.56
Health Care	198.07	Telecommunications	12.48
Financial Services	191.77	Construction Materials	11.50
Retail	191.11	Industrial Goods Services	9.35
Automobiles & Parts	189.40	Oil & Gas	8.58
Chemicals	188.25	Basic Resources	7.61
Insurance	186.61	Chemicals	5.55
Construction Materials	184.35	Technology	5.49
Banks	182.50	Health Care	4.89
Industrial Goods Services	170.44	Banks	3.44
Oil & Gas	168.71	Travel & Leisure	3.18
Travel & Leisure	157.96	Automobiles & Parts	3.03

Table 7

Percentage changes of MES

from 24.02.2020 to 20.08.2020		from 20.08.2020 to 16.04.2021	
Travel & Leisure	267.01	Travel & Leisure	69.71
Real Estate Price	199.90	Banks	47.28
Insurance	180.71	Media	44.40
Oil & Gas	179.65	Oil & Gas	42.60
Utilities	177.66	Insurance	39.29
Banks	175.07	Utilities	38.36

Table 7 cont.

from 24.02.2020 to 20.08.2020		from 20.08.2020 to 16.04.2021	
Media	159.14	Real Estate Price	37.36
Construction Materials	146.84	Food & Beverage	32.30
Industrial Goods Services	134.79	Retail	23.21
Automobiles & Parts	134.27	Construction Materials	18.36
Food & Beverage	130.71	Financial Services	17.33
Financial Services	128.05	Telecommunications	13.86
Telecommunications	121.20	Personal Goods	12.54
Personal Goods	97.25	Industrial Goods Services	10.67
Chemicals	93.51	Automobiles & Parts	5.80
Basic Resources	82.89	Technology	5.24
Retail	80.49	Basic Resources	4.90
Health Care	79.51	Health Care	4.81
Technology	77.11	Chemicals	1.20

According to the measure ΔCoVar changes exceed 150% for all sectors in the most critical period and 7 of them exceed 200%, with the Utilities (for both intervals this sector is characterized by the greatest change) sector at the top. In turn, Travel & Leisure is notable for its lowest percentage change, unlike the ranking of changes of MES. The changes in the subperiods of the first and second waves in respect to the pre-pandemic period are the highest for the Travel & Leisure sector. Regarding the bottom of Table 7, we note the Technology sector with a percentage change above 77% and the Chemicals sector with 1.2 % change.

6. Conclusions

With ΔCoVar and MES we can assess systemic risk contributions among financial and insurance institutions. Risk increases in crisis periods and the level of changes is often the subject of interest. Despite the similarity between the time series plots of both measures, the percentage of concordant pairs of daily rankings is on average equal to about 50%. The rankings also indicate poor stability, which is proven by rank correlation between consecutive days. We also note that rankings of the most and least risky sectors are different and depend on the choice of measure. If there is such compliance, it is very rare. Applying the structural breaks estimation method, we found specific dates very similar for all sectors and both measures. Constructing the rankings of sectors in terms of the highest and lowest mean values at specific intervals we also do not obtain compatibility. For both measures we note huge percentage changes in mean risk values, especially in the period from 24.02.2020 till 20.08.2020 compared to the previous period. The percentage changes for both intervals indicate the same riskiest sectors, but the indications of both measures are not consistent.

References

[1] Adrian, T. and Brunnermeier, M.K. (2011) 'CoVaR' NBER Working Paper, No. 17454.

[2] Adrian, T. and Brunnermeier, M.K. (2016) 'CoVaR', *American Economic Review*, vol. 106 (7), pp. 1705–1741.

[3] Arbeláez, H., Urrutia. J. and Abbas, N. (2001) 'Short-term and long-term linkages among the Colombian capital market indexes', *International Review of Financial Analysis*, vol. 10 (3), pp. 237–273.

[4] Bai, J. and Perron, P. (1998) 'Estimating and testing linear models with multiple structural changes', *Econometrica*, vol. 66, pp. 47–78.

[5] Bai, J. and Perron, P. (2003) 'Computation and analysis of multiple structural changes model', *Journal of Applied Econometrics*, vol. 18, pp. 1–22.

[6] Bauwens, L., Laurent, S. and Rombouts, J.V.K. (2006) 'Multivariate GARCH models: A survey', *Journal of Applied Econometrics*, vol. 21(1), pp. 79–109.

[7] Benoit, S., Colletaz, G., Hurlin, C. and Perignon, C. (2013) 'A Theoretical and Empirical Comparison of Systemic Risk Measures', HEC Paris Research Paper No. FIN-2014-1030.

[8] Bianchi, M.L. and Sorrentino, A.M. (2020) 'Measuring CoVaR: An Empirical Comparison', *Computational Economics*, vol. 55, pp. 511–528.

[9] Bollerslev, T. (1990) 'Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH approach', *Review of Economics and Statistics*, vol. 72, pp. 498–505.

[10] Brownlees, C.T. and Engle, R. (2012) 'Volatility, correlation and tails for systemic risk measurement', Available at SSRN, 1611229.

[11] Cappiello, L., Engle R.F. and Sheppard, K. (2006) 'Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns', *Journal of Financial Econometrics*, vol. 4(4), pp. 537–572.

[12] Engle, R.F. (2002) 'Dynamic Conditional Correlation', *Journal of Business and Economic Statistics*, vol. 20(3), pp. 339–350.

[13] Fabozzi, F.J., Stoyanov, S.V. and Svetlozar R.T. (2013) 'Computational aspects of portfolio risk estimation in volatile markets: a survey', *Studies in Nonlinear Dynamics and Econometrics*, vol. 17(1), pp. 103–120.

[14] Girardi, G. and Ergün, A.T. (2013) 'Systemic risk measurement: Multivariate GARCH estimation of CoVaR', *Journal of Banking & Finance*, vol. 37(8) 3169–3180.
[15] Gong, J., Wu, W., McMillan, D. and Shi, D. (2015) 'Non-parametric estimation of copula parameters: testing for time-varying correlation', *Studies in Nonlinear Dynamics & Econometrics*, vol. 19(1), pp. 93–106.
[16] Guloksuz, C.T. and Kumar, P. (2019) 'A new bivariate Archimedean copula with application to the evaluation of VaR', *Studies in Nonlinear Dynamics & Econometrics*, vol. 17(2), pp. 23–36.
[17] Gurgul, H. and Syrek, R. (2014) 'The relationship between WIG-subindexes: evidence from the Warsaw Stock Exchange', *Managerial Economics*, vol. 15(2), pp. 149–164.
[18] Gurgul, H., Mestel, R. and Syrek, R. (2017) 'MIDAS models in banking sector – systemic risk comparison', *Managerial Economics*, vol. 18(2), pp. 165–181.
[19] Higgins, B. (1988) 'Is a recession inevitable this year?', *Economic Review*, vol. 73(1), pp. 3–16.
[20] Kavussanos, M.G. and Dockery, E. (2001) 'A multivariate test for stock market efficiency: the case of ASE', *Applied Financial Economics*, vol. 5, pp. 573–584.
[21] Lagoarde-Segot, T. and Lucey, B. (2008) 'Efficiency in emerging markets--Evidence from the MENA region', *Journal of International Financial Markets*, vol. 18, pp. 94–105.
[22] Manner, H., Stark, F. and Wied, D. (2021) 'A monitoring procedure for detecting structural breaks in factor copula models', *Studies in Nonlinear Dynamics & Econometrics*, vol. 25(4), pp. 171–192.
[23] Niarchos, N.A., Alexakis, C. (2003) 'Intraday stock price patterns in the Greek stock exchange', *Applied Financial Economics*, vol. 13(1), pp. 13–22.
[24] Oh, D.H. and Patton, A.J. (2017) 'Time-Varying Systemic Risk: Evidence From a Dynamic Copula Model of CDS Spreads', *Journal of Business & Economic Statistics*, vol. 36(2), pp. 181–195.
[25] Panagiotidis, T. (2005) 'Market capitalisation and efficiency. Does it matter? Evidence from the Athens stock exchange', *Applied Financial Economics*, vol. 15, pp. 707–713.
[26] Patra, T. and Poshakwale, S.S. (2008) 'Long-run and short-run relationship between the main stock indexes: evidence from the Athens stock exchange', *Applied Financial Economics*, vol. 18, pp. 1401–1410.
[27] Ratner, M. (1996) 'Investigating the behaviour and characteristics of the Madrid stock exchange', *Journal of Banking and Finance*, vol. 20, pp. 135–149
[28] Sheppard, K.K. and Engle, R.F. (2001) 'Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH', NBER Working Paper No. 8554.
[29] Sklar, A. (1959) 'Fonctions de repartition á n dimensions et leurs marges', *Publications de l'Institut Statistique de l'Université de Paris*, vol. 8, pp. 229–231.

[30] Siourounis, G.D. (2002) 'Modelling volatility and test for efficiency in emerging capital markets: the case of the Athens stock exchange', *Applied Financial Economics*, vol. 1, pp. 47–55.
[31] Tse, Y.K. (2000) 'A test for constant correlations in a multivariate GARCH model', *Journal of Econometrics*, vol. 98(1), pp. 107–127.
[32] Tse, Y.K. and Tsui, A.K.C. (2002) 'A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations', *Journal of Business and Economic Statistics*, vol. 20(3), pp. 351–362.
[33] Wang, Z., Kutan, A. and Yang, J. (2005) 'Information flows within and across sectors in Chinese stock markets', *The Quarterly Review of Economics and Finance*, vol. 45, pp. 767–780.
[34] Xu, Q., Chen, L., Jiang, C. and Yuan, J. (2018) 'Measuring Systemic Risk of the Banking Industry in China: A DCC-MIDAS-t Approach', *Pacific-Basin Finance Journal*, vol. 51, pp. 13–31.

Summary

In this index study, the relationships between Stoxx Europe 600 and sector indices are analyzed. This research uses ΔCoVar and MES as analytical tools developed as a measure of systemic risk and applied to financial institutions, to sectoral subindexes. For the sake of systemic risk assessment we calculate the dynamic correlation model with bivariate *t* copula distribution. We focus on the impact of sectors on the market. Despite the similarity between the time series plots of both measures, with maximum values on similar days, the compatibility of daily rankings, measured as a percentage of concordant pairs, is equal to about 50%. The rankings of the most and least risky sectors are different and depend on the choice of measure, but in the case of both we observe poor stability. When sectors are ranked in terms of the highest and lowest mean values at specific intervals (designated by the structural break estimation method, which surpisingly detects very similar dates of structural changes) we draw the same conclusions. For both measures we note huge percentage changes in mean values of risk, especially in the period from February 24, 2020 till August 20, 2020 with respect to the previous period. The percentage changes for both intervals indicate the same most risky sectors, but the indications of both measures are not consistent.

JEL codes: G15, G19

Keywords: *Stoxx Europe 600 index, systemic risk, ΔCoVaR, MES, Covid-19 pandemic*