The Covid-19 effect on the volatility transmission of global financial markets

Sinem Derindere Koseoglu[a], Man Luo[b] and Andreas Tsopanakis[c]

[a]Bursa Technical University, Bursa, 16310, Turkiye, email: sinem.derindere@btu.edu.tr, tel: (+90) 2243003232

[b]School of Management, Zhejiang University, Zijingang Campus, Hangzhou, 310058, P.R. China, email: luoman@zju.edu.cn

[c]Economics Section, Cardiff Business School, Cardiff University, Aberconway Building, Colum Drive, CF10 3EU, Cardiff, UK, email: TsopanakisAG@cardiff.ac.uk

Abstract

Aim of this paper is the study of the impact covid-19 pandemic has on the volatility transmission between some major stock markets. The unprecedented effect of the global pandemic is considered as one of the major disruptions in the economic activity and investment opportunities around the world. The major economies affected by the global health crisis are investigated (namely, US, UK, China, Japan, Italy, Germany, Turkey, Belgium), using a multivariate GARCH framework. The model is enhanced with the inclusion of dummy variables capturing the potential informational impact of the covid cases and covid-related deaths in these markets. Overall, there seems to be limited life of the aforementioned events on the degree of information flow from one market to the other.

JEL Classifications: C43, G01, G15, F37

Keywords: Volatility Transmission, Covid-19 pandemic, Multivariate GARCH, Interconnectedness

1. Introduction

The current pandemic has led to an unprecedented response from governments, in terms of the extreme measures taken to contain the spread of the virus; this led to a strict economic lockdown, with detrimental effects on the national economies and international trade. Because of the pandemic, the OECD decreased its global GDP forecast in March 2020. According to the OECD Interim Economic Outlook Report[1], annual global GDP growth is estimated to drop to 2.4% in 2020 as a whole. It was already weak in 2019 at 2.9%. Besides, the IMF also revised its global economy estimates, it is forecasted to contract by 3% sharp decrease in the global economy in 2020.

The impact of the pandemic is evident also on the stock markets, with asset prices plummeting and remaining low for a significant amount of time. The major stock markets around the world reported huge declines due to the pandemic. The global stock market crash started in late February 2020. Between 20 February and 23 March 2020, many major stock indices dropped at least by 30%. The stock markets globally experienced their largest drop since the 2008 financial crisis. For instance, the DJIA, S&P 500, and Nasdaq dropped by 36.4%, 33,8 %, and 30% respectively. Similar declines experienced in major European indices too. FTSE 100 declined by 33% while DAX dropped by 36%. In the same period, Italy Stock Market reported the worst decline, the FTSE MIB dropped by 38% from 20 February and 23 March 2020.

After this crash, the volatility of global stock markets increased in a large extent. Due to the global financial markets are strongly interconnected, the Covid-19 pandemic can trigger a range of distress transmission to several major markets around the world.

The aim of the study is to investigate the degree at which the spread of the deadly coronavirus has initiated such waves of volatility transmission through the markets analyzed. This study is inspired from prior research, investigating the stress transmission effect of specific events or financial crisis affecting stock markets on a transnational, global scale. Caporale et al. (2006), Horta, Mendes & Vieira (2008), Hwang, In & Kim (2010), Naoui, Liouane & Brahim (2010), Baur (2011), Syllignakis & Kouretas (2011), Mollah, Zafirov & Quoreshi (2011), Kenourgios, Christopoulos & Dimitriov (2011) are among the examples of such studies. The results of such studies show that stock markets are significantly affected by these specific events and there are evident of contagion effects. The Dynamic Coditional Correlation (DCC) GARCH model is traditionally employed in studies of the contagion effect of specific events or financial crisis on stock markets, and this is the approach we also adopt.

Albulesco (2020) shows that the announcements of new cases infection and of death ratio both in China and outside China increase the financial volatility, whereas outside China triggers a more profound impact. Baker et al. (2020) investigate historical diseases effects on financial markets. The study

[1] Interim of Economic Assessment March (2020)

unravels that which infectious disease affect stock market volatility the most and Covid-19 has the most powerful effect on stock markets among all infectious disease outbreak in history.

In order to achieve our goal end, the study of the pandemic effect on stock markets volatility transmission, we employ the aforementioned multivariate GARCH model, where the baseline DCC model is enhanced using dummy variables for two particularly important events in the course of the covid-19 spread in these markets: the announcement of the first case and the announcement of the first death from the new virus. Our model resembles the one introduced by Tamakoshi and Hamori (2013). Our results give the degree of this volatility transmission, the magnitude and the directional effect of this transmission between the countries analysed.

2. Data and Empirical Approach

Our dataset consists of stock market returns for 10 major economies[2]. We choose the most significant market index for each one of these markets, as a strong indicator of each market's performance and returns. The period covered spans from March 2019 up until December 2022. Daily observations are used and data are retrieved by yahoo finance webpage. First differences of the market indexes are employed in order to capture the market returns and avoid any issues of potential non-stationarity of the original series.

In order to capture the potential impact of the covid pandemic outbreak, a number of dummy variables are employed. For each one of the countries in our sample, we construct two dummies: one capturing the first case effect and another one for the first death. These are the events representing a switch on the behaviour of our dummy variables. The dates, on which the first Covid19 case and the first death were observed for each market, are those provided by the World Health Organization.

The empirical strategy we follow entails the estimation of the Dynamic Conditional Correlation (DCC) model, as proposed by Engle (2002). This multivariate GARCH model is rather flexible, overcoming certain numerical difficulties other volatility models face and also because it is ideal for the estimation of time-varying co-movements of the markets. The model is specified as:

$$y_t = \mu_t(\theta) + \varepsilon_t$$

$$H_t = D_t R_t R_t$$

Where $y_t = (y_{it} \dots y_m)'$ is a nx1 vector of stock returns, $\mu_t(\theta)$ is the conditional mean vector of stock returns, specified as an ARMA process. $D_t = diag(h_{iit}^{\frac{1}{2}} \dots h_{nnt}^{\frac{1}{2}})$ is the diagonal matrix of square root conditional variances, each element of which is defined as a univariate GARCH-type model and R_t is a matrix containing the time-varying conditional correlations.

[2] These are: US, UK, China, Japan, Germany, France, Italy, Spain, Belgium, Turkey.

These conditional variances are used in the second step of our empirical design, in order to examine whether the aforementioned episodes of new cases and deaths in different countries might have a reinforcing effect on the degree of interdependence of the markets under investigation. In order to do this, we estimate a model of the following fashion:

$$CondVar_{it} = \beta_0 + \beta_1 c_t + \beta_2 d_t + \varepsilon_t$$

where i stands for each one of the markets under consideration, c_t is the dummy capturing the time when first covid case is officially announced and d_t the first covid death, in each country respectively. OLS regressions are estimated for each country, using their own dummies.

3. Empirical Results

Figure 1 exhibits the stock markets performance for the period under consideration. It is evident that there is a significant drop on the global market at the beginning of 2020, coinciding with the increasing uncertainty and spread of the coronavirus. In the majority of the cases, markets returned to pre-lockdown performance later on the following year, even though some markets turmoil lasted longer (for instance Spain or China). The volatile conditions are verified by graph 2, where 2020 is a period of intense volatility in the markets.

The correlation matrix provides an initial estimate of the potential interdependence of the market in our dataset. It is interesting to notice that Chinese stock market is closely tied to the Japanese, but not that much to the European ones. The same holds for the case of Turkey, where negative correlation coefficients are produced for almost all cases. On the other hand, European markets seem to be closely related, with correlations that are strong and positive. Table 2 provide some descriptives, indicating the rationale for employing a GARCH modelling approach for our empirical strategy.

Our models estimates are provided in tables 3 and 4. The former exhibits the DCC results, while the latter is a summary of the dummy regressions results. DCC seems to work well, with the exception of Turkey and the insignificant results for China. Overall, though, the model seems to be a good fit for our data and the model verifies the strong and significant ties of the markets under consideration. The correlation coefficient estimated are strongly significant, with clear evidence of strong market interdependence. As per the regression results, there seems to be a similar response on the covid first case and first death official announcements, as indicated in table 4. They both have strong and significant effect, strangely enough a negative one from the first death announcement. As it stands, the first death announcement, which obviously comes with a time lag compared to the announcement of the first covid case, seems to contribute as a factor reducing the degree of intensity of stock markets co-movement. Given the diagnostics provided, such as R-squared and the dummy trap issues for a couple of cases in our sample, further investigations are required in this stage of the empirical analysis.

Overall, our initial results suggest that global stock markets are rather immune to the announcement of the pandemic worsening. Even though there seems to be a jump on the volatility transmission upon the country's authorities' announcements of, either, an infection or death case, this increase is only transitory and dies out rather soon. This outcome is observed across the board of markets under investigation in this study.

4. Conclusions

The recent pandemic of 2020-2022 has brought unprecedented public health and economic policy measures, never seen before in the global economy. As a result, there is an imperative need to study further the potential impact of this once in a lifetime event to the economy and the stock markets performance in particular. Our aim is to explore whether the intensification of the covid crisis has had any significant impact on the degree of interconnectedness and interactions of a number of important stock markets around the world. Using data from 2019 up until 2022, we study the volatility transmission channel for ten markets, using a multivariate GARCH framework, namely the DCC model. There seems to be some notable increase in the conditional volatilities and variances of these markets, especially during the initial period of the pandemic outbreak. Nevertheless, this shock seems to be absorbed by the markets relatively soon, indicating investors' adjustment to the new norm. Dummy regressions are employed, in an effort to study the potential impact of the official announcements of the first covid case and covid death on the shifting volatility transmission in the markets. The very initial results, though still premature, indicate that there an unclear effect from these announcements, but further work is required to clarify this point.

References

To be added

Appendix

Figure 1: Stock market Indices

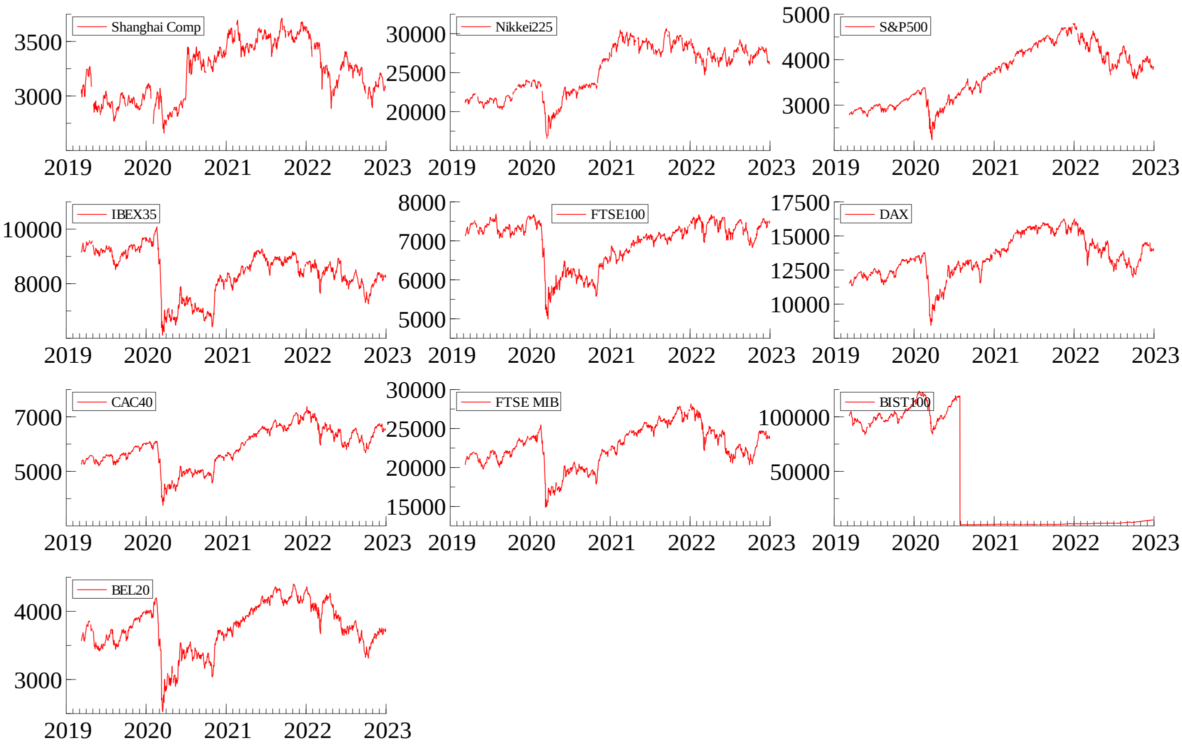

Figure 2: Stock market returns

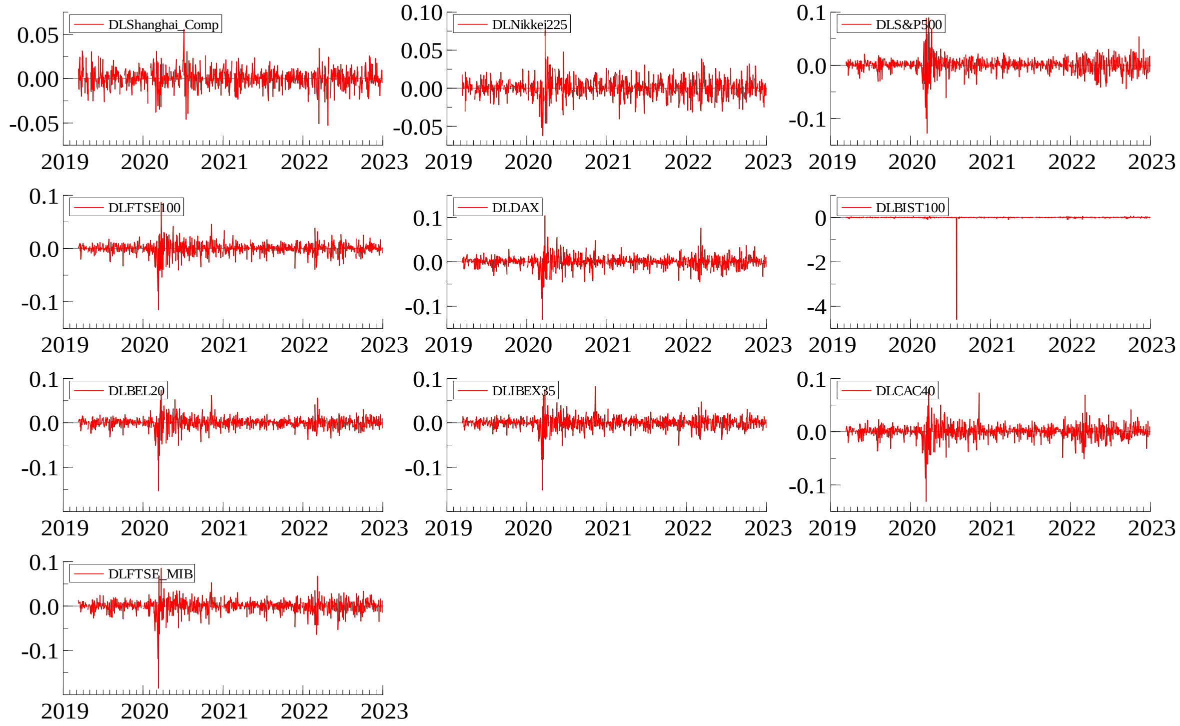

Figure 3: Conditional Variances

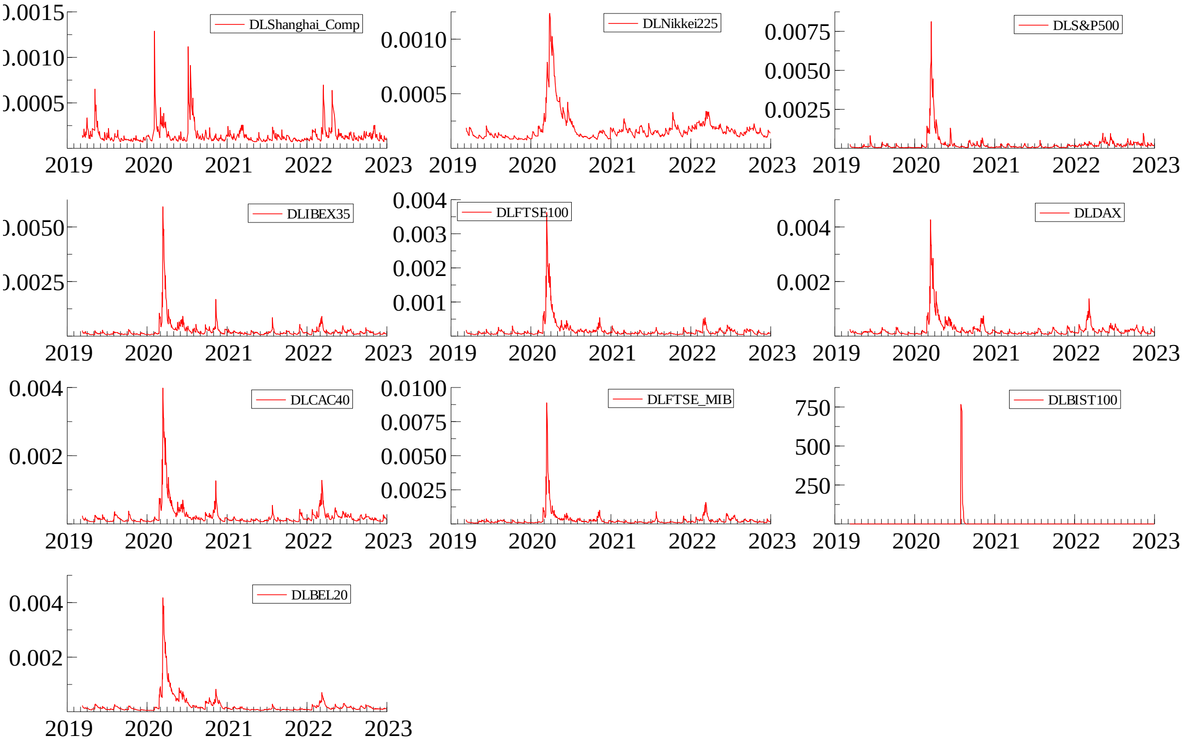

Table 1: Correlation Matrix

	Shanghai Comp	Nikkei225	S&P500	IBEX35	FTSE100	DAX	CAC40	FTSE MIB	BIST100
Shanghai Comp									
Nikkei225	0.796								
S&P500	0.792	0.917							
IBEX35	0.037	0.177	0.136						
FTSE100	0.045	0.349	0.358	0.829					
DAX	0.782	0.865	0.899	0.395	0.448				
CAC40	0.557	0.801	0.858	0.550	0.752	0.872			
FTSE MIB	0.606	0.763	0.810	0.641	0.699	0.914	0.952		
BIST100	-0.745	-0.815	-0.815	0.234	-0.018	-0.641	-0.532	-0.444	
BEL20	0.583	0.706	0.754	0.707	0.709	0.875	0.897	0.954	-0.353

Table 2: Descriptive Statistics of Stock Returns

	Shanghai Comp	Nikkei225	S&P500	IBEX35	FTSE100	DAX	CAC40	FTSE MIB	BIST100	BEL20
Mean	1.9142e-005	0.0002640	0.0004053	-0.000122	6.5249e-005	0.0002476	0.0002772	0.0002080	-0.003641	6.0443e-005
Standard Deviation	0.0119	0.0136	0.0158	0.0156	0.0130	0.0155	0.0153	0.0170	0.1636	0.0149
Skewness	-0.5241**	0.1839**	-0.8716**	-1.1612**	-1.003**	-0.5665**	-0.9308**	-2.0365**	-27.715**	-1.530**
Kurtosis	6.0815**	3.6617***	11.795**	14.827**	12.85**	11.733**	11.165**	22.265**	775.63**	18.161**
JB Test	1269.4**	451.45**	4739**	7507.8**	5638.4**	4631.9**	4271.1**	17077**	2.0156e+007	11306**
Q(10)	15.2624	21.91*	87.4346**	27.097**	30.6732**	29.1486**	21.91*	28.04**	0.3074	45.23**
$Q^2(10)$	40.1985**	387.444**	1144.14**	235.87**	433.08**	268.36**	304.436**	151.704**	0.0128	216.43**
ARCH(5)	2.4164*	28.705**	105.53**	29.521**	36.403**	25.171**	37.517**	21.79**	0.012	30.583**

Notes: Q(10) and $Q^2(10)$is the Ljung-Box statistic for serial correlation in raw and squared series, respectively.

Table 3: DCC-MGARCH(1,1) Estimation Results

Panel A: univariate GARCH estimates

	Shanghai Comp	Nikkei225	S&P500	IBEX35	FTSE100	DAX	CAC40	FTSE MIB	BIST100	BEL20
Constant (m)	0.0002	0.0006	0.0014**	0.0004	0.0003**	0.0008***	0.0009**	0.0009**	-0.03	0.0006
Constant (v)	0.1764	0.061**	0.108**	0.1402**	0.098***	0.131***	0.136***	0.148***	6.895**	0.052**
α	0.1756	0.0713***	0.3018**	0.2108***	0.1763***	0.1725***	0.1792***	0.2074***	36.2	0.1291***
β	0.7130***	0.8926***	0.6879***	0.7411***	0.7604***	0.7737***	0.7626***	0.75***	-0.004	0.8508***

Panel B: Dynamic Correlation (ρ_{ij}) estimates and diagnostic tests

	Shanghai Comp	Nikkei225	S&P500	IBEX35	FTSE100	DAX	CAC40	FTSE MIB	BIST100
Shanghai Comp									
Nikkei225	0.1806**								
S&P500	0.0240	0.1283**							
IBEX35	0.0408	0.1370**	0.4146***						
FTSE100	0.0588	0.1301*	0.3961***	0.6560***					
DAX	0.0439	0.1571**	0.4763***	0.7004***	0.6469***				
CAC40	0.0103	0.1332**	0.5068***	0.7912***	0.7515***	0.8219***			
FTSE MIB	0.0396	0.102	0.4917***	0.7784***	0.6537***	0.7592***	0.8471***		
BIST100	0.0280	-0.053	0.1178	0.1082	0.0978	0.1698*	0.1313	0.1442	
BEL20	0.0472	0.132**	0.4527***	0.0292***	0.6589***	0.723***	0.7869***	0.7357***	0.1516*
α					0.0159***				
β					0.9722***				
df					5.5495***				
log-likelihood					25516				
AIC					-63.52				
SIC					-62.8875				
H(20)					2425.17***				
H^2(20)					2371.38***				
Li-McLeod(20)					2422.59***				
Li-McLeod^2(20)					2367.77***				

Notes: H(20) and H^2(20) and Li-McLeod(20) and Li-McLeod ^{2}(20) are the multivariate versions of the Ljung-Box statistic for serial correlation in raw and squared series, respectively, as proposed by Hosking (1980) and Li and McLeod (1981).

Table 4: Dummy Regressions Results

	Shanghai Comp	Nikkei225	S&P500	IBEX35	FTSE100
Constant	0.000162146***	0.000167684***	0.000417638**	0.000351387***	0.000261251***
ct	0.000110886***	0.000515845***	9.99473e-005	9.37240e-005	2.46293e-005
dt	-0.000130662***	-0.000516895***	-0.000322141*	-0.000238665***	-0.000161485***
R2	0.01911	0.3510	0.03434	0.02666	0.05172
LogL	6133.26	6140.25	4817.61	5045.24	5413.71
	DAX	**CAC40**	**FTSE MIB**	**BIST100**	**BEL20**
Constant	0.000329573***	0.000310840***	0.000436250***	0.0463123***	0.000368843***
ct	0.000176486*	0.000163302	-0.000190738	-0.0375768***	-0.000207388**
dt	-0.000309542***	-0.000275875***		4.60833	
R2	0.04813	0.03168	0.02084	0.002743	0.06580
LogL	5231.12	5261.39	4810.84	-4105.67	5192.84