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Econometric Modeling of the Impact of the COVID-19 Pandemic on the Volatility of the Financial Markets †

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Abstract: The purpose of this paper is to identify econometric models likely to highlight the impact of the COVID-19 pandemic on the financial markets. The Markov-switching "GARCH and EGARCH" models are suitable for analyzing and forecasting the series of daily returns of the major global stock indices (i.e., SSE, S&P500, FTSE100, DAX, CAC40, and NIKKEI225) during the pre-COVID-19 period, from 1 June to 30 November 2019, and the post-COVID-19 period, from 31 December 2019, to 1 June 2020. The Markov-switching "GARCH and EGARCH" models allow good modeling of the conditional variance. The estimated conditional variance values by these models highlight the increase in volatility for the stock markets in our sample, during the post-COVID-19 period compared to that pre-COVID-19, with a peak in volatility in "early January 2020" for the Chinese stock market and in "March 2020" for the other five stock markets (i.e., New York, Paris, Frankfurt, London, and Tokyo). The stock exchange of Frankfurt has shown great resilience compared to other international stock exchanges (i.e., the stock exchanges in Paris, London, and New York). The modeling of the impact of the COVID-19 pandemic on the financial markets by the Markov-switching "GARCH and EGARCH" models makes it possible to simultaneously take into consideration the nonlinearity at the level of the mean and the variance, and to obtain the results of the transition probabilities, the unconditional probabilities and the conditional anticipated durations during the pre-COVID-19 period and the post-COVID-19 period.

Keywords: financial markets; Markov-switching GARCH models; COVID-19 pandemic; volatility

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1. Introduction

The prices of the main international financial market portfolios experienced a plunge in March 2020 due to the COVID-19 pandemic. Pandemics can also have a substantial impact on financial systems due to their enormous economic costs [1]. It is true that the previous literature remains limited as to how pandemics affect financial markets. However, some research has advanced the impact of the COVID-19 pandemic on financial volatility [2–4]. It should be noted that other forms of natural disasters, such as earthquakes and volcanoes; air disasters; as well as acts of terrorism, have a negative impact on financial markets [1,5–9]. Since the appearance of the first case of COVID-19 in Wuhan in December 2019, the virus has quickly spread to all corners of the world. On 11 March 2020, when it has already affected more than 100,000 people and killed thousands of people in over 100 countries, the World Health Organization (WHO) declared the coronavirus epidemic (COVID-19) as a global pandemic. The global spread of COVID-19, which has saturated healthcare systems, has forced societies and economies to shut down, causing social and economic disruption. The negative repercussions of the COVID-19 pandemic on foreign trade, tourism, transport, and industry were evident [10]. Its economic consequences are likely to exceed those of the global financial crisis of 2007–2009. In fact, in its April 2020 report, the International Monetary Fund forecasts a global growth rate of −3% in 2020, which is lower than the lowest rate of −1.7% recorded in 2009 during the global financial crisis of 2007–2009 [11]. The negative, substantial, and sudden impact of the COVID-19 pandemic on major stock markets was evident in March 2020 [1,10,12,13]. Indeed, the price of the S&P 500 stock index, which reached a high value of 3386.15 points on 19 February 2020, experienced, after almost a month, a decline of around 34% and recorded a low value of 2237.40 points on 23 March 2020. The price of FTSE 100 also registered a decline of about 30% for a single month and fell from 7403.9 points on 16 February 2020 to 5190.8 points on 15 March 2020. Likewise, the price of CAC 40 fell from 6111.24 points on 19 February 2020 to 3754.84 points on 18 March 2020, a drop of around 39% for a single month. The literature explains financial volatility through factors related to economic conditions, institutional problems, market uncertainty, good or bad announcements, and economic policy uncertainty [10,14–23]. There is a fair amount of research that has focused on estimating and forecasting the economic and financial costs of pandemics [1]. For example, the study of the economic costs of the HIV pandemic [24], the impact of the HIV pandemic on development [25], the costs of growing global obesity and diabetes [26], the work on forecasting the economic costs for possible future pandemics which has highlighted the importance of good health system management to address the people affected and tackling outbreaks as well as the negative impact of social distancing on economic activity [27], with the study indicating the need to prepare for pandemics and estimating the value of the annual losses due to a possible pandemic at around 500 billion US dollars, or 0.6% of global income [28]-currently considered to be underestimated [1]-the work highlighting the need for economic risk management versus potential probability future pandemics [29,30]. The objective of this paper is, therefore, to identify econometric models likely to model the processes of the series of daily returns of the main world stock market indices: SSE, S&P500, FTSE 100, DAX, CAC40, and NIKKEI 225, during the pre-COVID-19 period, from 1 June to 30 November 2019, and the post-COVID-19 period, from 31 December 2019 to 1 June 2020, in order to highlight the substantial impact of the COVID-19 pandemic on the financial markets. Since these series experience phases of calm or low volatility and phases of crisis or high volatility, the Markov-switching "GARCH and EGARCH" models constitute the econometric methods adequate to model their volatility during the period pre-COVID-19 and the post-COVID-19 one [31–36].

2. Results and Concluding Remarks

Both the graphical examination of our variables of interest and the unit root tests, i.e., the increased Dickey–Fuller, Phillips–Perron, and KPSS (Kwiatkovski, Phillips, Schmidt and Shin), show that the daily prices of the main world stock indices: SSE, S&P500, FTSE 100, DAX, CAC40, NIKKEI 225 are not stationary, while the series of daily returns of the same indices: RSSE, RS&P500, RFTSE 100, RDAX, RCAC40 and RNIKKEI 225, are stationary, during the pre-COVID-19 period and the post-COVID-19 one.

Tables 1–4 below present the results of the estimation of the Markov-switching "GARCH and EGARCH" models during the pre-COVID-19 and post-COVID-19 periods.

Given the results of the individual significance test of the coefficients, the information criteria (i.e., Bayesian Information Criteria (BIC)), and the Log-likelihood (Log(L)), the models suitable for modeling conditional volatility are, on the one hand, the Markov-switching EGARCH model, with normal distribution, for the RS&P500, RSSE, RDAX, RFTSE, and RNIKKEI series, the Markov-switching EGARCH model, with a generalized distribution of errors, for the RCAC series, during the pre-COVID-19 period; and, on the other hand, the Markov-switching EGARCH models, with normal distribution, for the RS&P500, RCAC, RFTSE, and RNIKKEI series, the Markov-switching EGARCH model, with a Student distribution, for the RDAX series, and the Markov-switching GARCH model, with normal distribution, for the RSSE series, during the post-COVID-19 period. Figure 1 below illustrates the graphical representations of the conditional volatilities estimated by the models indicated above, during the pre-COVID-19 period and the post-COVID-19 one, for the six series of our interest: RS&P500, RSSE, RDAX, RCAC, RFTSE, and RNIKKEI.

Table 1. Estimation of Markov-switching GARCH models during the pre-COVID-19 period from 1 June to 30 November 2019. $h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)}\varepsilon_{t-1}^2 + \beta^{(i)}h_{t-1}$. Where h_{t-1} is the independent state of the past conditional variance; $\alpha_0^{(i)} > 0, \alpha_1^{(i)} \geq 0 \wedge \beta^{(i)} \geq 0$, with $i \epsilon \{1;2\}$.

	RS&P500			RSSE			RDAX			RCAC			RFTSE			RNIKKEI 225		
	MS-nGARCH (Normal Distribution)	MS-sGARCH (Student Distribution)	MS-gedGARCH (GED Distribution)	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH
$\alpha_0^{(1)}$	0.0397	0.0432	0.0413	0.0000	0.0142	0.0194 *	0.0594 *	0.0559	0.0583	0.0399	0.0300	0.0340	0.0219	0.1495	0.0196	0.2008 **	0.2442	0.2685
$\alpha_0^{(2)}$	0.2507 **	0.2244	0.2421 *	0.0000	0.0003	0.0001	0.1674 **	0.1194	0.1380	0.2722 *	0.1586	0.2093	0.0266	0.0001	0.0198	0.0000 ***	0.0001	0.0001
$\alpha_1^{(1)}$	0.0397	0.0432	0.0413	0.0004	0.0142 *	0.0194	0.0594	0.0559	0.0583	0.0399 *	0.0300	0.0340	2.3633	1.1209	3.4992	0.2008 ***	0.2442	0.2686
$\alpha_1^{(2)}$	0.2507 *	0.2244 *	0.2421	0.0367	0.0003	0.0001	0.1674 *	0.11943	0.1380	0.2722 **	0.1586	0.2093	0.0009	0.0032	0.0013	0.0000 ***	0.0001	0.0001
$\beta_1^{(1)}$	0.6836 ***	0.6959 ***	0.6860 ***	0.9999 ***	0.9800 ***	0.9724 ***	0.7545 ***	0.8025 ***	0.7770 ***	0.7090 ***	0.8119 ***	0.7623 ***	0.8962 ***	0.4959	0.9139 ***	0.6985 ***	0.6582 ***	0.5945 **
$\beta_1^{(2)}$	0.6837 ***	0.8787 ***	0.6860 ***	0.9632 ***	0.9800 ***	0.9724 ***	0.7545 ***	0.8025 ***	0.7770 ***	0.7090 ***	0.8119 ***	0.7624 ***	0.0229	0.1810	0.0920	0.6985 ***	0.6582 ***	0.5945 *
$v^{(1)}$		8.4613 *	1.5233 *		6.7499 **	1.4285 ***		4.8566	1.3430 **		3.9446 **	1.1658		99.7120 ***	3.7656 ***		4.6154 ***	1.3526 ***
$v^{(2)}$		8.4615 *	1.5233 *		6.7499 ***	1.4285 ***		4.8564 *	1.3430 ***		3.9447	1.1659 *		6.9040	19.9959 ***		4.6154 **	1.3525 ***
P_{11}	0.9708 ***	0.9204 ***	0.9708 ***	0.4511 ***	0.0000	0.5745 ***	0.9635 ***	0.9135 ***	0.9135 ***	0.9174 ***	0.9481 ***	0.9174 ***	0.9675 ***	0.9687 ***	0.9623 ***	0.5000 ***	0.5936 ***	0.5000 **
P_{21}	0.0796 ***	0.0292	0.0796 **	1.0000	0.4255 ***	1.0000 ***	0.0865 ***	0.0365	0.0365	0.0519 **	0.0826	0.0519	0.3088 **	0.1067 ***	0.6949 ***	0.4064 ***	0.5000 ***	0.4064 *
Log(L)	−133.3526	−131.4676	−131.982	−145.6943	−149.1706	−149.2006	−153.8733	−149.0492	−150.3224	−151.7521	−142.9516	−144.7371	−131.3101	−132.3429	−128.8778	−147.0999	−144.4282	−144.4264
BIC	305.3954	311.2981	312.3268	329.8209	346.3814	346.4414	346.5001	346.5403	349.0866	342.3827	334.5014	338.0724	301.4365	313.2061	306.276	332.632	336.8965	336.893

*: indicates the significance of the coefficient at the statistical threshold of 10%; **: indicates the significance of the coefficient at the statistical threshold of 5%; and ***: indicates the significance of the coefficient at the statistical threshold of 1%.

Table 2. Estimation of Markov-switching GARCH models during the post-COVID-19 period from 31 December 2019 to 1 June 2020. $h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)}\varepsilon_{t-1}^2 + \beta^{(i)}h_{t-1}$. Where h_{t-1} is the independent state of the past conditional variance; $\alpha_0^{(i)} > 0, \alpha_1^{(i)} \geq 0 \wedge \beta^{(i)} \geq 0$, with i $\epsilon\{1;2\}$.

	RS&P500			RSSE			RDAX			RCAC			RFTSE			RNIKKEI 225		
	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH
$\alpha_0^{(1)}$	0.1409	0.0878	0.1153	1.0390 **	0.0252	1.6457	0.2328 **	0.0282	0.1110	0.1191 *	0.0000	0.3499	0.1872	0.0000	0.5019	0.2429	0.2229	4.2051
$\alpha_0^{(2)}$	0.2992 *	0.2813	0.2932	0.9999 ***	0.0708	0.9999 ***	0.1970 **	0.1047	0.1470	0.5735 *	0.1619	0.2245	0.2845	0.1756	0.2298	0.1816 **	0.1743	0.9998 ***
$\alpha_1^{(1)}$	0.1409	0.0878	0.1153	1.0390 *	0.0252 **	1.6460 **	0.2329	0.0282	0.1110	1.1660 *	0.0000	0.3499	0.1874 *	0.0000	0.5019	0.2429	0.2229	4.2051
$\alpha_1^{(2)}$	0.2992 **	0.2813 *	0.2932	0.9999 ***	0.0708	0.9999 ***	0.1970	0.1048	0.1470	0.1796	0.1619	0.2245	0.2852 **	0.1757	0.2298 *	0.1816	0.1743	0.9998 ***
$\beta_1^{(1)}$	0.6498 ***	0.6764 ***	0.6601 ***	0.0000 ***	0.9143 ***	0.0000	0.7566 ***	0.8787 ***	0.8172 ***	0.3134 ***	0.8380 ***	0.7214 ***	0.6637 ***	0.8242 ***	0.7074 ***	0.7526 ***	0.7641 ***	0.0001
$\beta_1^{(2)}$	0.6498 ***	0.6764 ***	0.6601 ***	0.0000 ***	0.9143 ***	0.0000	0.7566 ***	0.8787 ***	0.8172 ***	0.7291 ***	0.8380 ***	0.7215 ***	0.6631 ***	0.8242 ***	0.7074 ***	0.7526 ***	0.7641 ***	0.0001
$v^{(1)}$		11.1271 **	1.6108 ***		3.2933 **	0.7000 ***		4.5435 ***	1.0829		4.8549 ***	0.7000 ***		6.6031 ***	0.7000 ***		11.3866	0.7000 ***

Table 2. *Cont.*

	RS&P500			RSSE			RDAX			RCAC			RFTSE			RNIKKEI 225		
	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH	MS-nGARCH	MS-sGARCH	MS-gedGARCH
$\upsilon^{(2)}$		11.1273 **	1.6108 ***		3.2936	0.7000 ***		4.5434	1.0829 ***		4.8545	0.7000 ***		6.5993	0.7000 ***		11.3867	0.7000 ***
P_{11}	0.9747 ***	0.9747 ***	0.9820 ***	0.9624 ***	0.9624 ***	0.9013	0.9992 ***	0.9992 ***	0.9715 ***	0.9834 ***	0.9996	0.9996 ***	0.9724 ***	0.9996	0.9724 ***	0.9813 ***	0.9596 ***	0.9596
P_{21}	0.0180 **	0.0180	0.0253 ***	0.0987 ***	0.0987 ***	0.0376	0.0285 ***	0.0285 ***	0.0008	0.0120	0.0276	0.0276 ***	0.0004	0.0276	0.0004	0.0404 ***	0.0187	0.0187
Log(L)	−216.1008	−214.935	−215.2672	−164.8534	−156.4963	−161.0797	−233.2177	−224.3603	−225.0192	−218.9026	−218.1442	−227.0016	−215.6416	−210.3256	−220.6903	−199.1081	−198.6219	−206.969
BIC	469.2794	476.2174	476.8816	366.3045	358.7397	367.9064	503.5132	495.068	496.3858	474.9604	482.7323	500.4472	468.3611	466.9985	487.7279	434.8139	442.991	459.6852

*: indicates the significance of the coefficient at the statistical threshold of 10%; **: indicates the significance of the coefficient at the statistical threshold of 5%; and ***: indicates the significance of the coefficient at the statistical threshold of 1%.

Table 3. Estimation of Markov-switching EGARCH models during the pre-COVID-19 period from 1 June to 30 November 2019. $log\left(h_t^{(i)}\right) = \alpha_0^{(i)} + \alpha_1^{(i)}\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \alpha_2^{(i)}\frac{\varepsilon_{t-1}}{h_{t-1}} + \beta^{(i)}log(h_{t-1})$. Where $i \epsilon \{1, 2\}$ and h_{t-1} is the independent state of the past conditional variance.

	RS&P500			RSSE			RDAX			RCAC			RFTSE			RNIKKEI 225		
	MS-nEGARCH	MS-sEGARCH	MS-gedEGARCH	MS-nEGARCH	MS-sEGARCH	MS-ged-EGARCH	MS-nEGARCH	MS-sEGARCH	MS-ged-EGARCH	MS-nEGARCH	MS-sEGARCH	MS-ged-EGARCH	MS-nEGARCH	MS-sEGARCH	MS-ged-EGARCH	MS-nEGARCH	MS-sEGARCH	MS-ged-EGARCH
$\alpha_0^{(1)}$	−0.0311	−0.0334	−0.0326	−0.1773	−0.1448	−0.1549	−0.0116 ***	−0.0023 ***	−0.0093	−0.0153 ***	−0.0022	−0.0114 ***	−1.1020 ***	−0.0620 ***	−0.0654 ***	−0.1106 ***	−0.0637 ***	−0.0813 ***
$\alpha_0^{(2)}$	−0.0311	−0.0334	−0.0325	−0.1773	−0.1448	−0.1549 ***	−0.0115 ***	−0.0023 ***	−0.0085	−0.0153 ***	−0.0022	−0.0114 ***	−0.2666 **	−0.0606 ***	−0.0737 ***	−0.1101 ***	−0.0637 ***	−0.0813 ***
$\alpha_1^{(1)}$	0.2485 ***	0.2491 ***	0.2502 ***	−0.3709 ***	−0.3586 **	−0.3712 *	−0.2009 ***	−0.2288 ***	−0.1436 ***	−0.2602 ***	−0.2275 ***	−0.2284 ***	0.4673 ***	−0.3216 ***	−0.3363 ***	−0.5506 ***	−0.5615 ***	−0.4395 ***
$\alpha_1^{(2)}$	0.2485 ***	0.2491 ***	0.2502 ***	−0.3709 ***	−0.3586 *	−0.3712 **	−0.2009 ***	−0.2288 ***	−0.1438 ***	−0.2602 ***	−0.2275 ***	−0.2284 ***	−1.4492 ***	−0.2780 ***	−0.3501 ***	−0.5509 ***	−0.5615 ***	−0.4395 ***
$\alpha_2^{(1)}$	−0.3162 ***	−0.3259 ***	−0.3204 ***	−0.1616**	−0.1374	−0.1467	−0.2628 ***	−0.2543 ***	−0.2025 ***	−0.3680 ***	−0.4195 ***	−0.3489 ***	0.3644 ***	−0.2453 ***	−0.2596 ***	−0.1819 ***	−0.2344 ***	−0.1823 ***
$\alpha_2^{(2)}$	−0.3162 ***	−0.3259 ***	−0.3204 ***	−0.1616**	−0.1374	−0.1467	−0.2628 ***	−0.2543 ***	−0.2026 ***	−0.3680 ***	−0.4195 ***	−0.3489 ***	−1.2816 ***	−0.2606 ***	−0.3138 ***	−0.1820 ***	−0.2344 ***	−0.1823 ***
$\beta_1^{(1)}$	0.9138 ***	0.9103 ***	0.9123 ***	0.5603 ***	0.6049 ***	0.5893 ***	0.9427 ***	0.9491 ***	0.9504 ***	0.9345 ***	0.9268 ***	0.9336 ***	0.0895 *	0.9088 ***	0.9071 ***	0.7769 ***	0.8058 ***	0.8172 ***
$\beta_1^{(2)}$	0.9138 ***	0.9103 ***	0.9123 ***	0.5603 ***	0.6049 ***	0.5893 ***	0.9427 ***	0.9491 ***	0.9504 ***	0.9345 ***	0.9268 ***	0.9336 ***	0.3108 ***	0.9079 ***	0.8950 ***	0.7769 ***	0.8058 ***	0.8172 ***
$\upsilon^{(1)}$		24.3579 ***	1.8826 ***		7.4575 ***	1.4773 ***		4.8542 ***	0.9504 ***		4.3069 ***	1.5106 ***		6.3084 ***	1.4212 ***		5.6409 ***	1.7891 ***
$\upsilon^{(2)}$		24.3579 ***	1.8826 ***		7.4575 ***	1.4773 ***		4.8542 ***	0.9504 ***		4.3069 ***	1.5106 ***		6.3110 ***	1.3899 ***		5.6409 ***	1.7891 ***
P_{11}	0.9708 ***	0.9708 ***	0.9708 ***	0.5745 ***	0.5745 ***	0.0000	0.9635 ***	0.9635 ***	0.9135 ***	0.9481 ***	0.9174 ***	0.9481 ***	0.9148 ***	0.5002 ***	0.5014 ***	0.5000 ***	0.5936 ***	0.5000 ***
P_{21}	0.0796 ***	0.0796 ***	0.0796 ***	1.0000 ***	1.0000 ***	0.4255 ***	0.0865 ***	0.0865 ***	0.0365 ***	0.0826 ***	0.0519 ***	0.0826 ***	0.3550 ***	0.5002 ***	0.5009 ***	0.4064 ***	0.5000 ***	0.4064 ***
Log(L)	−123.5262	−123.4272	−123.476	−148.5441	−146.9717	−147.1036	−140.0383	−139.6108	−140.959	−138.0418	−133.0186	−132.0914	−126.9224	−128.758	−128.2535	−131.8982	−132.0324	−132.3902
BIC	295.4153	304.8897	304.9874	345.1284	351.5917	351.8555	328.5185	337.3519	340.0481	324.6817	324.3549	322.5006	302.365	315.7403	314.7314	311.8367	321.7131	322.4287

*: indicates the significance of the coefficient at the statistical threshold of 10%; **: indicates the significance of the coefficient at the statistical threshold of 5%; and ***: indicates the significance of the coefficient at the statistical threshold of 1%.

Table 4. Estimate of EGARCH regime change models during the post-COVID-19 period from 31 December 2019 to 1 June 2020. $log\left(h_t^{(i)}\right) = \alpha_0^{(i)} + \alpha_1^{(i)}\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \alpha_2^{(i)}\frac{\varepsilon_{t-1}}{h_{t-1}} + \beta^{(i)}log(h_{t-1})$. Where $i \epsilon \{1,2\}$ and h_{t-1} is the independent state of the past conditional variance.

	RS&P500			RSSE			RDAX			RCAC			RFTSE			RNIKKEI 225		
	MS-nEGARCH	**MS-sEGARCH**	**MS-gedEGARCH**	**MS-nEGARCH**	**MS-sEGARCH**	**MS-ged-EGARCH**	**MS-nEGARCH**	**MS-sEGARCH**	**MS-ged-EGARCH**	**MS-nEGARCH**	**MS-sEGARCH**	**MS-ged-EGARCH**	**MS-nEGARCH**	**MS-sEGARCH**	**MS-ged-EGARCH**	**MS-nEGARCH**	**MS-sEGARCH**	**MS-ged-EGARCH**
$\alpha_0^{(1)}$	−0.0158 ***	−0.0118 *	−0.0151 ***	0.0257	0.0385	0.0261	−0.0006	−0.0008	−0.0001	−0.0167 ***	−0.0139	−0.0101 ***	−0.0134 ***	−0.0117 ***	−0.0099 ***	0.0149 ***	0.0082 ***	0.0141 ***
$\alpha_0^{(2)}$	−0.0157 ***	−0.0116 *	−0.0151 ***	0.0258	0.0385	0.0261	−0.0006	−0.0008	−0.0001	−0.0167 ***	−0.0139	−0.0101 ***	−0.0134 ***	−0.0117 ***	−0.0099 ***	0.0151 ***	0.0084 ***	0.0142 ***
$\alpha_1^{(1)}$	−0.4035 ***	−0.3505 *	−0.3677 ***	0.0542	0.0405	0.0464	−0.1609 ***	−0.1560 ***	−0.1461 ***	−0.2236 ***	−0.2022 ***	−0.2031 ***	−0.1686 ***	−0.1764 ***	−0.2013 ***	−0.1915 ***	−0.1706 ***	−0.2003 ***
$\alpha_1^{(2)}$	−0.4035 ***	−0.3505 **	−0.3677 ***	0.0542	0.0405	0.0464	−0.1609 ***	−0.1560 ***	−0.1461 ***	−0.2236 ***	−0.2022**	−0.2031 ***	−0.1686 ***	−0.1764 ***	−0.2013 ***	−0.1915 ***	−0.1707 ***	−0.2003 ***
$\alpha_2^{(1)}$	−0.7525 ***	−0.6938 ***	−0.7034 ***	−0.7902 ***	−0.6965 **	−0.7399 **	−0.2850 ***	−0.2914 ***	−0.2875 ***	−0.3796 ***	−0.3974 ***	−0.3351 ***	−0.316 ***	−0.3271 ***	−0.3036 ***	−0.2588 ***	−0.2667 ***	−0.2965 ***
$\alpha_2^{(2)}$	−0.7521 ***	−0.6932 ***	−0.7034 ***	−0.7902 ***	−0.6965	−0.7399	−0.2850 ***	−0.2914	−0.2875 ***	−0.3796 ***	−0.3974 ***	−0.3351 ***	−0.316 ***	−0.3271 ***	−0.3036 ***	−0.2587 ***	−0.2665 ***	−0.2965 ***
$\beta_1^{(1)}$	0.9561 ***	0.9609 ***	0.9597 ***	0.7145 ***	0.7429 ***	0.7251 ***	0.9801 ***	0.9858 ***	0.9839 ***	0.9761 ***	0.9778 ***	0.9810 ***	0.9825 ***	0.9841 ***	0.9868 ***	0.9699 ***	0.9778 ***	0.9679 ***
$\beta_1^{(2)}$	0.9561 ***	0.9609 ***	0.9597 ***	0.7145 ***	0.7429 ***	0.7251 ***	0.9801 ***	0.9858 ***	0.9839 ***	0.9761 ***	0.9778 ***	0.9810 ***	0.9825 ***	0.9841 ***	0.9868 ***	0.9699 ***	0.9778 ***	0.9679 ***
$\upsilon^{(1)}$		55.0694 ***	2.3187 ***		5.3726 ***	1.3823 ***		5.1847 ***	1.3514 ***		6.2915 ***	1.5078 ***		7.0457 ***	1.5115 ***		29.1137 ***	1.9323 ***
$\upsilon^{(2)}$		55.0694 ***	2.3187 ***		5.3726 ***	1.3823 ***		5.1847 ***	1.3514 ***		6.2915 ***	1.5078 ***		7.0457 ***	1.5115 ***		29.1137 ***	1.9323 ***
P_{11}	0.9747 ***	0.9747 ***	0.9820 ***	0.9624 ***	0.9624 ***	0.9624 ***	0.9715 ***	0.9992 ***	0.9715 ***	0.9724 ***	0.9724 ***	0.9724 ***	0.9724 ***	00.9724 ***	0.9724 ***	0.9813 ***	0.9596 ***	0.9596 ***
P_{21}	0.0180 ***	0.0180 ***	0.0253 ***	0.0987 ***	0.0987 ***	0.0987 ***	0.0008 ***	0.0285 ***	0.0008 ***	0.0004 ***	0.0004	0.0004 ***	0.0004 ***	0.0004 ***	0.0004 ***	0.0404 ***	0.0187 ***	0.0187 ***
Log(L)	−201.2783	−201.4655	−201.0586	−151.7309	−150.2307	−150.0951	−216.7804	−214.6281	−215.3432	−209.9184	−209.109	−209.8444	−202.4837	−201.7522	−201.9135	−188.9213	−188.9126	−188.6964
BIC	448.9038	458.5478	457.734	349.2089	355.3579	355.0866	479.9082	484.8729	486.3032	466.2807	473.9507	475.4216	451.3147	459.1211	459.4438	423.5896	432.7216	432.2894

*: indicates the significance of the coefficient at the statistical threshold of 10%; **: indicates the significance of the coefficient at the statistical threshold of 5%; and ***: indicates the significance of the coefficient at the statistical threshold of 1%.

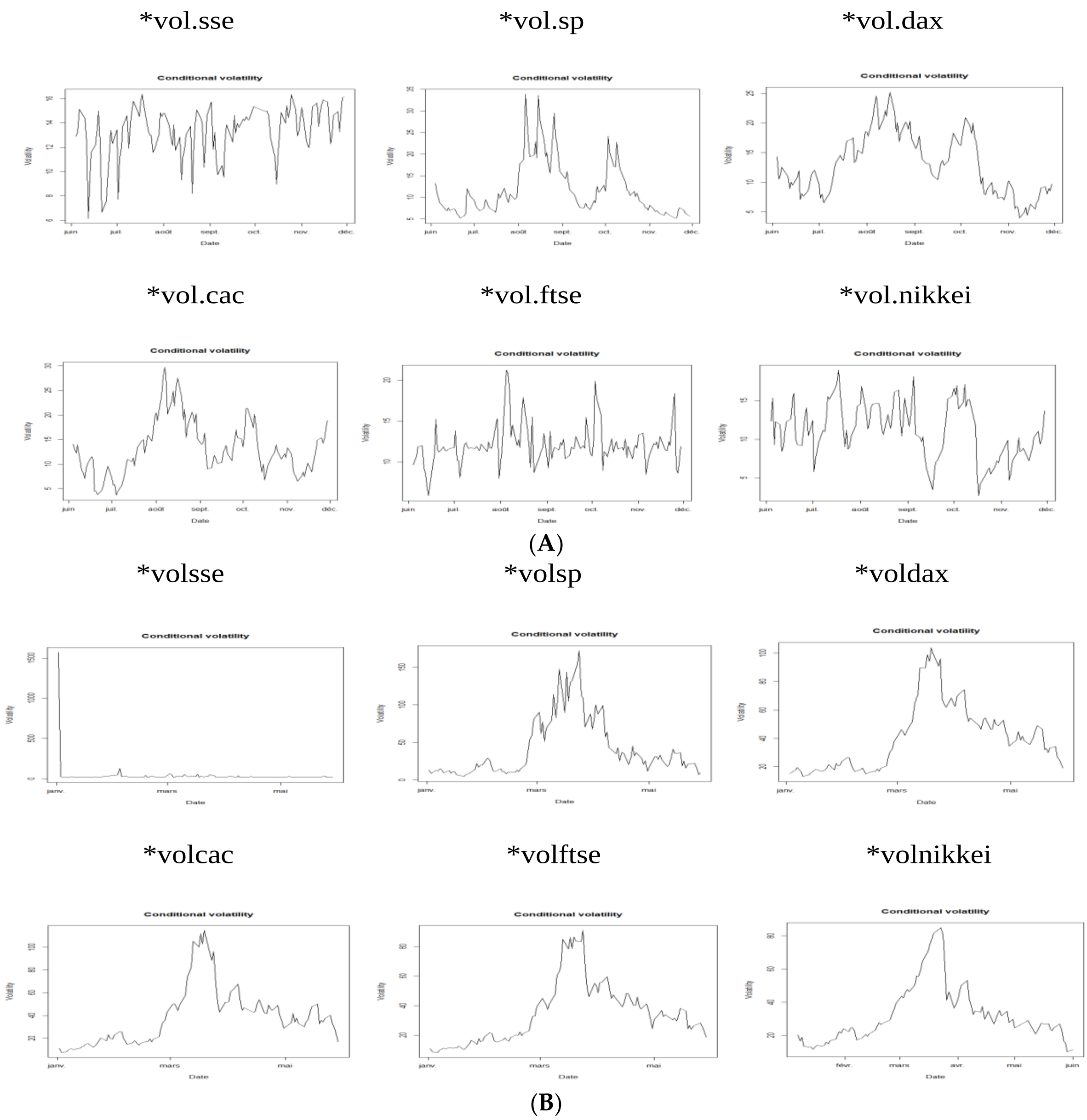

Figure 1. Conditional volatility during the pre-COVID-19 and post-COVID-19 period. (**A**) Pre-COVID-19 period from 1 June to 30 November 2019. (**B**) Post-COVID-19 period from 31 December 2019 to 1 June 2020.

From this figure, we see that the extent (maximum-minimum) is very large during the post-COVID-19 period compared to the pre-COVID-19 period. Apart from the stock market of the epicenter country of the COVID-19 pandemic (the Chinese stock market), for which conditional volatility (denoted “volsse”) reached its peak in “late December-early January” during the post-COVID-19 period, volatilities conditions of the other five stock markets (the New York, Paris, Frankfurt, London, and Tokyo stock exchanges) reached their climax in March 2020. This finding clearly illustrates the increase in volatility in the main stock markets due to the pandemic of COVID-19.

The indicators of central tendency and position (the first quartile, the median, the third quartile, the arithmetic mean), the minimum value, the maximum value, and the dispersion indicators (the standard deviation, the coefficient of variation, and the interquartile range) of conditional volatility (Tables 5 and 6) increased during the post-COVID-19 period compared to the pre-COVID-19 period. This increase clearly illustrates the increase in volatility in major stock markets due to the COVID-19 pandemic.

Table 5. Statistical indicators of conditional volatility during the pre-COVID-19 period.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Std. Dev.	Interquartile Coefficient
S&P	5.134	7.262	9.663	11.77	14.275	33.858	6.263305	0.725758046
SSE	6.156	12.171	13.616	13.218	14.766	16.375	2.089393	0.190584606
DAX	3.962	8.628	12.042	12.961	17.328	25.193	5.18288	0.72247135
CAC	3.682	9.25	12.389	13.273	16.346	29.703	5.59991	0.572766164
FTSE	5.849	10.977	11.667	11.963	12.457	21.238	2.40386	0.126853518
NIKKEI	2.672	8.664	11.171	11.195	14.086	18.974	3.578993	0.485363889

Table 6. Statistical indicators of conditional volatility during the post-COVID-19 period.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Std. Dev.	Interquartile Coefficient
S&P	4.89529	13.23112	27.1176	42.77574	62.66145	172.00951	39.30484	1.822813597
SSE	16.12	16.9	19.17	40.42	26.43	1569	157.4888	0.497130934
DAX	13.31	19.29	37.62	40.35	52.3	103.76	23.27155	0.877458799
CAC	7.773	17.917	34.91	38.874	49.572	114.521	25.16885	0.906760241
FTSE	8.316	17.32	31.563	34.389	45.535	90.947	20.76365	0.893926433
NIKKEI	10.06	21.05	27.23	32.47	39.47	85	17.08098	0.676459787

According to the values of the transition probability P_{21}, we see that the chances of passing from the state of crisis at t-1 to the state of stability at t have greatly decreased, during the post-COVID-19 period compared to that pre-COVID-19, for all stock markets in our sample (Tables 7 and 8). For example, this probability goes, between the pre-COVID-19 and post-COVID-19 period, from 0.355 to 0.0004 for the stock exchange of London, from 0.4064 to 0.0404 for the stock exchange of Tokyo, and from 0.0826 to 0.0004 for the stock exchange of Paris. It should be noted that the stock exchange of Frankfurt recorded the smallest decrease in this probability between the pre-COVID-19 and the post-COVID-19 period, a drop from 0.0865 to 0.0285. Based on the values of the unconditional probability in the stable state π_1 and the unconditional probability in the crisis state π_2, we see that the COVID-19 pandemic has had a negative impact on the stock exchanges of New York, Paris, and London. In other words, the proportion of observations that should be in a state of crisis (π_2) increased significantly, during the post-COVID-19 period compared to the pre-COVID-19 period, for these three stock exchanges. Between the pre-COVID-19 and post-COVID-19 period, this proportion rose from 19.35% to 98.57% for the stock exchange of London, from 38.59% to 98.57% for the stock exchange of Paris, and from 26.84% to 58.43% for the stock exchange of New York. In return, the stock exchange of Frankfurt showed great resilience, compared to other international stock exchanges, with the recording of a very low value of the unconditional probability of the state of crisis π_2 and a very high value of the unconditional probability of the state of stability π_1, during the post-COVID-19 period compared to the pre-COVID-19 period. In fact, the proportion of observations that should be in the state of crisis increased from 38.59%, during the pre-COVID-19 period, to 2.73%, during the post-COVID-19 period, for this stock exchange. It should also be noted that, to a lesser extent, the stock exchange of Tokyo has also shown a certain resilience, with a decrease in the proportion of observations that should be in the state of crisis during the post-COVID-19 period compared to the pre-COVID-19, or 31.64% against 55.16%. These latest results are supported by the variations in the values of the expected duration conditional on the state of crisis and the expected duration conditional on the state of stability, namely: the significant increase in the expected period of high volatility ($1/1 - P_{22}$) during the post-COVID-19 period compared to that pre-COVID-19 for the stock exchanges of Paris, London, and New York, as well as the significant increase in the expected period of low volatility ($1/1 - P_{11}$) during the post-COVID-19 period compared to that pre-COVID-19 for the stock exchange of Frankfurt. On the one hand, we can expect a period of high volatility equal to 2500 days, or 1.6 years, during the post-COVID-19 period against a period of high volatility equal, respectively, to almost 12 days and 3 days during the pre-COVID-19 period for stock exchanges in Paris and London. On the other hand, we can expect a period of high volatility equal to only 35 days during the post-COVID-19 period against a period of high volatility equal to almost 11 days during the pre-COVID-19 period for the stock exchange of Frankfurt. The resilience of this stock exchange in relation to the COVID-19 pandemic is illustrated by the expected period of low volatility equal to 1250 days, or 0.8 years, during the post-COVID-19 period, against an expected period of low volatility equal to 27 days, during the pre-COVID-19 period, for the German stock market.

Table 7. Transition probabilities, unconditional probabilities, and conditional anticipated duration (the pre-COVID-19 period).

Transition Probabilities, Unconditional Probabilities and Conditional Anticipated Duration	**RS&P500**	**RSSE**	**RDAX**	**RCAC**	**RFTSE**	**RNIKKEI225**
P_{11}	0.9708	0.5745	0.9635	0.9481	0.9148	0.5
$P_{22} = 1 - P_{21}$	0.9204	0	0.9135	0.9174	0.645	0.5936
$P_{12} = 1 - P_{11}$	0.0292	0.4255	0.0365	0.0519	0.0852	0.5
P_{21}	0.0796	1	0.0865	0.0826	0.355	0.4064
$\pi_1 = \frac{1-P_{22}}{2-P_{22}-P_{11}}$	0.7316	0.7015	0.7033	0.6141	0,8065	0.4484
$\pi_2 = \frac{1-P_{11}}{2-P_{22}-P_{11}}$	0.2684	0.2985	0.2967	0.3859	0.1935	0.5516
Conditional anticipated duration on the state of crisis = $1/1 - P_{22}$	12.5628	1.0000	11.5607	12.1065	2.8169	2.4606
Conditional anticipated duration on the state of stability = $1/1 - P_{11}$	34.2466	2.3502	27.3973	19.2678	11.7371	2.0000

Table 8. Transition probabilities, unconditional probabilities, and conditional anticipated duration (the post-COVID-19 period).

Transition probabilities, Unconditional Probabilities, and Conditional Anticipated Duration	**RS&P500**	**RSSE**	**RDAX**	**RCAC**	**RFTSE**	**RNIKKEI225**
P_{11}	0.9747	0.9624	0.9992	0.9724	0.9724	0.9813
$P_{22} = 1 - P_{21}$	0.982	0.9013	0.9715	0.9996	0.9996	0.9596
$P_{12} = 1 - P_{11}$	0.0253	0.0376	0.0008	0.0276	0.0276	0.0187
P_{21}	0.018	0.0987	0.0285	0.0004	0.0004	0.0404
$\pi_1 = \frac{1-P_{22}}{2-P_{22}-P_{11}}$	0.4157	0.7241	0.9727	0.0143	0.0143	0.6836
$\pi_2 = \frac{1-P_{11}}{2-P_{22}-P_{11}}$	0.5843	0.2759	0.0273	0.9857	0.9857	0.3164
Conditional anticipated duration on the state of crisis = $1/1 - P_{22}$	55.5556	10.1317	35.0877	2500.0000	2500.0000	24.7525
Conditional anticipated duration on the state of stability = $1/1 - P_{11}$	39.5257	26.5957	1250.0000	36.2319	36.2319	53.4759

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