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How COVID-19 has affected stock market persistence?
Evidence from the G7’s
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ARTICLE INFO

Article history:
Received 20 April 2021
Received in revised form 20 June 2021
Available online 2 July 2021

Keywords:
COVID-19
Volatility
Persistence
Conditional variance
G7
FIGARCH

ABSTRACT

This paper examines how COVID-19 pandemic has affected volatility persistence in the G7’s stock markets. Based on daily data we divided the whole sample into two sub-samples according to its breakpoints and found that they occurred right after the declaration of COVID-19 pandemic by the World Health Organization — WHO (2020). This approach allows us to assess the main differences between these two distinct phases. Thus, while the first sub-period is relatively calm, the second one, which coincides with the pandemic outbreak, shows higher levels of volatility. Considering this, we rely on GARCH-type models to assess the degree of persistence of volatility and to evaluate how it has evolved across sub-samples. Our results show that the FIGARCH(1,d,1) is the best model to describe the data and that the degree of persistence is very different from the first to the second sub-sample. Thus, while the pre-pandemic period exhibits lower levels of persistence it has greatly increased with the COVID-19 outbreak. In particular, S&P 500 and FTSE/MIB became the most persistent indices in contrast to NIKKEI 225 and FTSE 100, which were amongst the least persistent.

1. Introduction

The outbreak of COVID-19 in Wuhan (China) in the end of 2019 has rapidly widespread to the rest of the World, severely affecting the regular functioning of the global economy as a whole. Since then, the number of confirmed cases has grown continuously, having surpassed as of 15 April 2021 136,000,000 cases and 2,900,000 deaths, with more than 230 countries suffering from this condition [1]. Its distinct nature, which has led governments to respond with lockdowns, social distancing and travel bans has halted economic activity giving rise to unprecedented levels of uncertainty. Never before a medical crisis, has had so many adverse consequences. Mensi et al. [2] even claim that it has more negative repercussions than the Global Financial Crisis (GFC) of 2008 or SARS-COV-1. Indeed, unlike other serious diseases (e.g. avian influenza, H1N1 influenza, MERS) the novel coronavirus has a high contagious rate, which has made it transcend the local borders of China, triggering a new strand of research focused on the impact of health emergencies in the economy (see [2–14], for some references). This has negatively affected stock markets, which in turn became more volatile and unpredictable [3,4]. Of particular interest in this debate is the degree of persistence of shocks to the volatility process and how do they behaved before and after the outburst of COVID-19. Understanding this phenomenon is critical because persistent changes in volatility may affect investors’ exposure to risk and, consequently, determine the expected

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https://doi.org/10.1016/j.physa.2021.126210
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risk-return premium. As volatility is an important input in many pricing models, its degree of persistence also affects derivative and asset valuations, thus influencing hedging and speculating strategies. Furthermore, long memory has also implications on the elasticity of stock market prices with respect to volatility [15].

Specifically in this study, we investigate if this pandemic has changed the degree of persistence of the G7’s stock market volatility and, if so, to what extent. We focus on these markets, as they constitute a benchmark for the whole World. To the best of our knowledge, this was not yet been addressed before. Indeed the related literature on the impact of COVID-19 on financial markets has concentrated mainly on the determinants of volatility [3–5], its asymmetric effects [2,6–9], the rate of contagion among markets [10] and the role of some assets (e.g., cryptocurrencies, commodities) as a hedge/safe haven in this turbulent period [11–13], somehow neglecting its potential long memory effects. Our study overcomes this limitation.

The phenomenon of persistence was first documented in Hydrology by Hurst [16,17] when studying the flow of the river Nile. In Finance, one of the earliest studies belongs to Mandelbrot [18] who alerted to the slowly decline of the autocorrelation function of some return series, implying that effects to the volatility process tend to endure over time. Consequently, as markets do not immediately react to the arrival of new information but rather progressively, observations are not independent and therefore, can be used to predict future returns. This is crucial for finance as it entails predictability of returns and can imply that crisis tend to endure over time. Such phenomenon is especially relevant in the post-COVID era as a way to understand if this is a temporary meltdown or, on the contrary, constitutes a structural recession. Thus, measuring persistence is of utmost importance as it may help speculators, hedgers and regulators to devise strategies to deal with its adverse consequences. For a detailed debate on the duration of market crises, see Bentes [19].

Although prior studies have investigated the persistence of stock market volatility and, in particular, how it has been affected during turbulent financial periods, such as the Asian crisis or the GFC [20–24], the implications of COVID-19 on stock market persistence has yet to be addressed. The only exception is Szczygielski et al. [14]: however, they only focus on the persistence of google search terms related to financial turmoil after the pandemic outbreak and not on the stock market volatility itself, as we do. In general, the vast majority of researches regarding the persistent nature of financial crises concluded that stock market volatility increased during financial turmoil due to the sentiment of investors that tend to replicate previous investing strategies.

On the other hand, empirical studies in Econophysics have relied mainly on the estimation of the Hurst exponents to examine the persistent nature of data [25–28]. However, another methodology that has proven to be effective in describing this property, representing an innovation when compared to the former is the GARCH-type (Generalized Autoregressive Conditional Heteroscedasticity) framework, which takes into account the temporal variation of volatility. In particular, the FIGARCH model (Fractionally Integrated GARCH of Baillie et al., [29]) is quite useful because it is a flexible approach that allows for an intermediate range of persistence captured by the fractional differential parameter \( d \) and accommodates both the GARCH \( (d = 0) \) and the IGARCH – Integrated GARCH \( (d = 1) \) models, as special cases. Note that while the GARCH framework postulates that shocks die at a fast exponential rate, the IGARCH on the other hand, accounts for infinite persistence.

In this study, we proceed in the following steps. First, we divide the whole sample into two sub-samples according to the structural breaks evidenced by the return series. This is important for two reasons. One is that ignoring regime shifts may overestimate the degree of persistence. Two, it allows us to evaluate how COVID-19 pandemic has affected stock market persistence. Second, we proceed with the estimation of the GARCH(1,1), IGARCH(1,1) and FIGARCH(1,d,1) models for both sub-periods to conclude about the persistence of the G7’s market volatility. In general, our results are consistent with previous empirical findings [30,31] and show that the degree of persistence vary according to regions and economic cycles. Specifically, we found that while the pre-pandemic phase is characterized by lower levels of volatility and minor persistence rates, they greatly increased with the outbreak of COVID-19. In particular, S&P 500 and FTSE/MIB were amongst the most persistent indices during this period.

Overall, our research is the first that investigates the degree of persistence of the G7’s stock market volatility in the pandemic phase and contribute to the literature in the following ways. First, it fills-in the existing gap related to the lack of empirical researches in this domain. Second, it adds to the current literature by shedding some light on the response of stock markets to COVID-19, in particular, in what concerns the effects on the persistence of volatility. Third, while previous literature identifies intrinsic financial factors as a source of volatility persistence, such as the GFC or the Asian crisis, which were generated within the financial system, our findings widens the debate on this topic by showing that it can also be due to exogenous factors, such as a health crisis.

The remainder of the paper is structured as follows: the next Section describes the methodological approach. Section 3 presents the data and discusses de results, finally Section 4 concludes.

2. Methodological approach

Persistence is an important feature of financial time series as it implies dependence between distant observations. In such situation, observations are not independent and therefore can be used to predict future returns, thus affecting the potential predictability of a time series. Although, this phenomenon was originally discovered in Hydrology [16,17], it has long been recognized to play an important role in finance [18], where it usually manifests by an hyperbolically decay of the autocorrelation function, which dissipates very slowly and eventually dies out [23].
To search for persistence in the G7’s main stock indices we rely on a FIGARCH \((1, d, 1)\) approach, derived by Baillie et al. [29], which accommodates both the GARCH and the IGARCH models, as special cases. Although these models became quite popular in describing the conditional volatility, they also show some drawbacks. Thus, while the original GARCH only accounts for short memory processes as it considers that shocks decay at a fast geometric rate, the IGARCH model on the other hand, allows for infinite persistence, a very unrealistic assumption.

Recall that the GARCH \((p, q)\) approach of Bollerslev [32] postulates for the mean equation
\[
e_t = z_t \sqrt{\sigma_t}, \quad z_t \sim N(0, 1),
\]
and for the variance
\[
\sigma_t^2 = \omega + \alpha (L) \varepsilon_t^2 + \beta (L) \sigma_t^2,
\]
where \(L\) denotes the lag or backshift operator, such that \(\alpha (L) \equiv \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_q L^q\) and \(\beta (L) \equiv \beta_1 L + \beta_2 L^2 + \cdots + \beta_q L^q\); \(\omega\) is the constant term. Notice that for stability and covariance stationarity, all roots of \([1 - \alpha (L) - \beta (L)]\) and \([1 - \beta (L)]\) must lie outside the unit circle.

Eq. (2) can be rewritten in the form of an ARMA \((m,p)\) model as
\[
[1 - \alpha (L) - \beta (L)] \varepsilon_t^2 = \omega + [1 - \beta (L)] \nu_t,
\]
where \(m \equiv \max (p, q)\), and \(\nu_t \equiv \varepsilon_t^2 - \sigma_t^2\) is mean zero serially uncorrelated.

According to this construction, the conditional variance \(\sigma_t^2\) depends not only on the lagged squared errors \(\varepsilon_{t-1}^2\) but also on the historical values of the variance itself \(\sigma_{t-1}^2\), therefore being suited to describe the volatility clustering phenomenon characterized by large/small changes in the return series being followed by other large/small changes [18].

A common empirical finding in related literature is that \(\alpha + \beta\) is usually close to unity thus implying that shocks may tend to persist over time. To describe this phenomenon, Bollerslev and Engle [33] derived the IGARCH\((p,q)\) model, given by
\[
\phi (L) (1 - L) \varepsilon_t^2 = \omega + [1 - \beta (L)] \nu_t,
\]
where \(\phi (L) \equiv [1 - \alpha (L) - \beta (L)] (1 - L)^{-1}\) is of order \(m - 1\), to capture infinite persistence. Thus, while the GARCH class of models characterizes short memory processes, the IGARCH on the other hand, describe infinite memory phenomena where shocks never die out.

In order to formulate a more flexible alternative that allows for an intermediate range of persistence, Baillie et al. [29] derived the FIGARCH\((p, d, q)\) class of models simply by replacing the first differencing operator in Eq. (4) with the fractional differencing operator. This model can be written as
\[
\sigma_t^2 = \omega + [1 - \beta (L)]^{-1} \{1 - [1 - \beta (L)]^{-1} \phi (L) (1 - L)^d\} \varepsilon_t^2,
\]
where \(0 \leq d \leq 1\) is the fractional difference parameter that captures the degree of persistence of the volatility process. Its main advantages is that it accommodates both the GARCH \((d = 0)\) and the IGARCH \((d = 1)\), as special cases, and allows for an intermediate range of persistence. The parameters of this model can be estimated by an approximate quasi-maximum likelihood technique [34].

3. Data and results

Our dataset consists of the daily closing prices of the G7’s main stock market indices, namely, S&P/TSX (Canada), CAC 40 (France), DAX 30 (Germany), FTSE/MIB (Italy), NIKKEI 225 (Japan), FTSE 100 (UK) and S&P 500 (US) retrieved from DataStream database. The sample period runs from March 4, 2019 to March 18, 2021 and is divided into two sub-periods: (i) before COVID-19 and (ii) during COVID-19 pandemic. This data split is important to understand how the market evolved across these distinct phases and how this health crisis has affected volatility persistence. To determine the breakpoint in the return series we employ the Perron [35] approach and found the following dates: (i) March 12, 2020 for S&P/TSX and FTSE/MIB; March 16, 2020 for CAC 40 and S&P 500; (iii) March 24, 2020 for DAX 30; (iv) March 27, 2020 for NIKKEI 225, and (v) March 23, 2020 for FTSE 100. Not surprisingly all breakpoints occurred in a short time interval following the declaration on March 11, 2020 of COVID-19 as a pandemic by WHO [1].

Our analysis relies on the continuously compounded returns computed as the percentage log-differences between prices at time \(t\) and \(t - 1\). Fig. 1 shows the dynamics of the G7’s return series for the overall sample. The graphical analysis reveals that the peaks approximately occur at the same time for all series highlighting the presence of sudden changes in the middle of March, which coincides with the declaration of COVID-19 pandemic. In addition, there is also evidence of co-movements among indices, suggesting spillover effects and a high degree of market integration. In comparison with the pre-pandemic period, high levels of volatility are also visible during the COVID-19 phase, which are particularly evident for the S&P/TSX and FTSE/MIB, two of the most affected economies by this global crisis. Overall, this figure clearly illustrates the presence of volatility clusters and the arising of two distinct periods, therefore justifying the use of GARCH-type models and the separation of the whole sample into sub-samples.

Table 1 reports the preliminary statistics of the S&P/TSX, CAC 40, DAX 30, FTSE/MIB, NIKKEI 225, FTSE 100 and S&P 500 for the pre-pandemic (Panel A) and during COVID-19 pandemic (Panel B) phases. In both sub-periods, we observe an
average return very small when compared to the variables standard’s deviation. Noteworthy, while in the pre-pandemic period all indices exhibit negative returns, the opposite occurs after the COVID-19 outbreak where higher average returns dominate. Likewise, soaring levels of volatility were also found in this period with the exception of NIKKEI 225, which was less volatile during the pandemic outbreak. The explanation for this may lie in the fact that Asian countries like Japan are more acquainted to health emergencies (e.g. avian influenza, H1N1 influenza, MERS, SARS-COV-1, etc.) than the western economies and have developed throughout the years mechanisms to deal with its consequences, therefore not being so severely affected [36,37]. In addition, we also found evidence of skewness and excess kurtosis in both sub-periods indicating that all series have thicker tails than the Normal. Note, however, that while in the first period six out of seven indices display negative skewness implying higher chances of making losses, results are mixed for the second half where only three indices display negative asymmetry, but of a lower magnitude. Similarly, kurtosis is also less pronounced in this sub-period. The rejection of the null hypothesis of the Jarque–Bera test for Gaussianity [38] at the 1% level, in all cases, confirms these results.

To assess the stationarity of the returns we apply the ADF (Augmented Dickey and Fuller [39]) and KPSS (Kwiatkowski, Philips, Schmidt and Shin [40]) tests. Our results show that all returns are stationary for the pre and during COVID-19 outbreak. Moreover, the Ljung–Box (Q) (Ljung and Box [41]) and Breusch–Godfrey (BG) tests (Breusch [42] and Godfrey [43]) indicate the presence of serial correlation in the data. Thus, we will need to fit an ARMA model to remedy this problem of the series. Finally, the rejection of both the Ljung–Box test of the squared residuals ($Q^2$) (McLeod and Li [44]) and the ARCH-LM test (Engle [45]) show that irrespective of the sub-period all series display conditional heteroskedasticity, therefore legitimizing the use of ARCH-type models.

Table 2 summarizes the estimated results of the ARMA-GARCH models for the G7’s returns across both sub-periods. As discussed above, we adjusted an ARMA (Autoregressive Moving Average) model to capture the serial correlation present in the data. Thus, an AR(1) specification for S&P/TSX and FTSE/MIB, an ARMA (2,2) for the CAC 40 and an ARMA(1,1) for DAX 30, NIKKEI 225, FTSE 100 and S&P 500 were fitted proving to be sufficient to overcome this limitation. To deal with the observed heteroskedasticity and to search for volatility clustering and persistence we employ a GARCH(1,1) process, which has shown to outperform other model specifications in theoretical and applied work [46–49]. Our results demonstrate that
### Table 1
Preliminary analysis of the G7’s index returns.

|                           | Descriptive statistics and Jarque–Bera test | Unit root tests | Serial correlation tests | Heteroskedasticity tests |
|---------------------------|----------------------------------------------|-----------------|--------------------------|--------------------------|
|                           | Mean                          | SD              | Skewness | Kurtosis | J.B. test | ADF       | KPSS       | Q-stat | BG       | Q²-stat | ARCH-LM     |
| **Panel A – Pre-pandemic period** |                               |                 |          |          |           |           |            |        |          |        |             |
| S&P/TSX                   | −0.0443                       | 0.9289          | −6.4109  | 72.2327  | 55348.70  | −2.9594   | 0.1966     | 47.0650 | 9.9558   | 17.5780 | 38.2450 ** |
| CAC 40                    | −0.0910                       | 1.3505          | −4.7115  | 40.0429  | 16435.90  | −6.0101   | 0.2151     | 38.9480 | 4.4140   | 43.3630 | 77.8613 ** |
| DAX 30                    | −0.1026                       | 1.4465          | −3.8354  | 29.9690  | 9040.96   | −9.6578   | 0.4485     | 45.5780 | 3.5002   | 63.8020 | 28.2759 ** |
| FTSE MIB                  | −0.0535                       | 1.2933          | −3.4277  | 28.9051  | 8018.45   | −12.7982  | 0.2000     | 48.9890 | 5.0060   | 19.2110 | 30.0848 ** |
| NIKKEI 225                | −0.0524                       | 1.2826          | 0.2301   | 13.4026  | 1260.44   | −13.3749  | 0.1049     | 33.2150 | 4.5501   | 204.3800 | 41.4031 ** |
| FTSE 100                  | −0.1142                       | 1.2605          | −4.0748  | 32.2924  | 10592.79  | −9.7945   | 0.1914     | 32.3810 | 3.7439   | 121.7200 | 18.2284 ** |
| S&P 500                   | −0.0124                       | 1.4070          | −1.2313  | 22.0791  | 4163.36   | −2.3670   | 0.2824     | 55.6660 | 9.4674   | 229.9800 | 133.4857 ** |
| **Panel B – During pandemic period** |                               |                 |          |          |           |           |            |        |          |        |             |
| S&P/TSX                   | 0.1044                        | 1.8977          | −1.1573  | 21.7393  | 3951.43   | −5.8949   | 0.0325     | 104.7600 | 6.9038   | 218.5200 | 20.3578 ** |
| CAC 40                    | 0.1465                        | 1.7111          | −1.8831  | 6.9332   | 171.73    | −10.7247  | 0.0431     | 30.9390 | 2.0291   | 112.8300 | 2.8452 **  |
| DAX 30                    | 0.2035                        | 1.6720          | 0.7760   | 9.0881   | 424.34    | −17.1729  | 0.1242     | 24.1950 | 1.8760   | 26.8260 | 1.8850 **  |
| FTSE MIB                  | 0.1030                        | 1.8911          | −1.0886  | 13.6244  | 1303.60   | −7.4852   | 0.0327     | 55.6080 | 3.3265   | 17.1750 | 3.5019 **  |
| NIKKEI 225                | 0.1889                        | 1.2525          | 0.0110   | 0.9072   | 38.65     | −10.4775  | 0.0588     | 23.2940 | 1.8380   | 43.6740 | 2.6721 **  |
| FTSE 100                  | 0.1031                        | 1.5155          | 0.4555   | 7.4644   | 224.04    | −8.2402   | 0.1010     | 26.0050 | 2.1276   | 59.7610 | 1.8197 **  |
| S&P 500                   | 0.1392                        | 1.7191          | −1.0229  | 16.0747  | 1926.46   | −6.2165   | 0.0321     | 83.8990 | 5.1321   | 96.7890 | 10.9539 ** |

Notes: J.B. denotes the Jarque–Bera test for normality [38]. ADF and KPSS are the Augmented Dickey–Fuller and Kwiatkowski, Philips, Schmidt and Shin tests, respectively. Q symbolizes the Ljung–Box test applied to the returns [41], while Q² symbolizes the Ljung–Box statistics of the squared residuals [44]. BG is the Breusch–Godfrey test [42, 43] for serial correlation and ARCH-LM refers to the Lagrange Multiplier test for homoscedasticity [45]. **Denotes significance at 1%. *Denotes significance at 5%. 
Table 2
Estimates and diagnosis tests of the ARMA-GARCH(1,1) model.

| Panel A — Pre-pandemic period | Mean equation | Variance equation | LL | Diagnosis tests |
|--------------------------------|---------------|------------------|----|----------------|
|                                | \( c \)       | \( \varphi_1 \)  | \( \varphi_2 \)  | \( \theta_1 \) | \( \theta_2 \) | \( \omega \) | \( \alpha \) | \( \beta \) | \( \alpha + \beta \) | Q-stat | ARCH-LM | Q\(^2\)-stat |
| S&P/TSX                        | 0.0985        | **0.2033**       | * -             | -             | -            | 0.0054  | 0.4843  | **0.6332** | **1.9661** | -155.1152 | 10.733  | 0.2337  | 5.2496   |
| CAC 40                         | 0.0758        | -0.7859          | **-0.5193**     | **0.8666**    | **0.5854**   | 0.0250  | 0.3803  | **0.6982** | **2.1778** | -317.6362 | 5.1281  | 0.3651  | 6.4634   |
| DAX 30                         | 0.1266        | -0.1337          | * -             | 0.1467        | -            | 0.0525  | 0.4760  | **0.6176** | **2.2674** | -361.8812 | 4.0772  | 1.3031  | 9.5987   |
| FTSE MIB                       | 0.0602        | 0.2398           | * -             | -             | -            | 0.1239  | 0.3437  | **0.5235** | **0.0198** | -354.4958 | 6.8812  | 0.2945  | 7.4531   |
| NIKKEI 225                     | 0.0023        | -0.5692          | * -             | **0.1230**    | *            | 0.1312  | **0.2398** | **0.6553** | **2.6853** | -366.2852 | 11.067  | 0.0485  | 8.4375   |
| FTSE 100                       | 0.0501        | 0.4877           | **-0.7859**     | **-0.5193**   | **0.8666**   | 0.0250  | 0.3803  | **0.6982** | **2.1778** | -317.6362 | 5.1281  | 0.3651  | 6.4634   |
| S&P 500                        | 0.1376        | -0.3135          | **-0.5643**     | * -            | 0.3492       | 0.0244  | 0.5168  | **0.5780** | **1.7181** | -277.4116 | 8.0692  | 0.0242  | 4.7097   |

| Panel B — During pandemic period | Mean equation | Variance equation | LL | Diagnosis tests |
|---------------------------------|---------------|------------------|----|----------------|
| S&P/TSX                         | 0.0985        | **0.5643**       | * -             | -             | -            | 0.0629  | 0.1937  | **0.7314** | **3.9256** | -360.9262 | 5.031   | 0.2005  | 8.8819   |
| CAC 40                          | 0.0925        | -0.3502          | **-0.1861**     | **0.2799**    | **0.2098**   | 0.0906  | 0.1515  | **0.7989** | **1.8902** | -441.7193 | 4.6676  | 0.0044  | 5.7497   |
| DAX 30                          | 0.0894        | -0.3161          | * -             | 0.2097        | -            | 0.1231  | 0.1346  | **0.7910** | **3.5119** | -434.0371 | 3.434   | 0.5122  | 6.3503   |
| FTSE MIB                        | 0.1343        | -0.8234          | * -             | -             | -            | 0.0799  | 0.0395  | **0.9888** | **3.0408** | -457.9622 | 2.2939  | 0.0433  | 5.3813   |
| NIKKEI 225                      | 0.1649        | -0.4390          | * -             | **-0.4871**   | **-0.4987**  | 0.1109  | 0.0966  | **0.8101** | **2.5498** | -393.3867 | 3.0322  | 0.3636  | 7.5774   |
| FTSE 100                        | 0.0646        | 0.4443           | * -             | -0.4724       | -            | 0.3497  | 0.1289  | **0.9871** | **5.1858** | -443.5531 | 4.8929  | 2.1862  | 9.7187   |
| S&P 500                         | 0.1613        | **0.2424**       | * -             | **-0.4036**   | *            | 0.0840  | **0.2040** | **0.7350** | **2.6711** | -406.2792 | 8.1923  | 0.6830  | 5.1077   |

Notes: This table reports the results of the quasi-maximum likelihood estimation of the ARMA-GARCH class model for the daily returns of the G7’s main stock market indices. \( c \) and \( \omega \) refer to the constant terms of the mean and variance equations, respectively. \( \varphi_1 \) and \( \varphi_2 \) are the parameters of the AR(1) and AR(2) autoregressive models, while \( \theta_1 \) and \( \theta_2 \) represent the parameters of the MA(1) and MA(2) moving average processes. \( LL \) represents the Log-likelihood function. Q-stat is the empirical statistics of the Ljung-Box test [41] up to 12 lags. ARCH-LM denotes the Engle [45] test for homoscedasticity up to 12 lags and Q\(^2\)-stat symbolizes the Ljung-Box statistics of the squared residuals [44] up to 12 lags.

**Indicates significance at 1% level.

*Indicates significance at 5% level.
except from the constant, all coefficients are positive and statistically significant at any of the standard levels highlighting the presence of volatility clusters in the G7’s returns. Moreover, higher GARCH coefficients (β) associated with the degree of persistence were also found for the COVID-19 sub-period, indicating that shocks tended to dissipate slowly after the pandemic outbreak. In Panel B, for instance, we notice that FTSE/MIB exhibits the highest coefficient-β (0.9888), while it shows the lowest (0.5235) in Panel A. The non-rejection of the Wald test with the null hypothesis of α + β = 1 for all series and periods, as shown by the insignificance of the Chi-square statistics, confirms this evidence. Similar conclusions also arise for the pre-pandemic period, suggesting that the return series may follow an IGARCH process characterized by infinite persistence. These results are in accordance with previous empirical findings, which document the persistent nature of shocks to the volatility process induced by a sum of the coefficients ARCH (α) and GARCH (β) very close to unity (see [50], inter alia). Following Mantegna and Stanley [51], we transformed α + β in terms of calendar days and found that the degree of memory ranged from 64.5 to 68.9 trading days in the first period and from 68.1 to 77.8 trading days in the second one, thus corroborating the higher level of persistence of the last sub-period. Our findings also show that ARCH effects are greater in the pre-pandemic period. We note, for example, that while S&P 500 exhibited the highest coefficient-α (0.5168) in Panel A, it fell down more than 50% (0.2040) in Panel B. For an exhaustive explanation on the interpretation of the ARCH/GARCH coefficients, refer to Alexander [52]. Overall, while the GARCH effects were larger in the second sub-period, the reverse occurred in the first sub-sample with the ARCH effects, which were found to be more pronounced before the pandemic outbreak.

As suggested by these results the next step was to estimate the ARMA–IGARCH model to account for persistence. Following the related literature, our choice fell on the IGARCH(1,1) specification given its supremacy when compared to alternative specifications [29]. Table 3 reports the results. As shown, the parameters α and β in the conditional variance equation are positive and highly significant. The only exception is the constant term, which is significant in nine out of 14 cases (except from Germany in Panel A and France, Japan, UK and US in Panel B). In general, a similar pattern to the GARCH(1,1) model was found when we compare coefficients α and β in both Panels, i.e., β tend to be higher in the COVID-19 sub-period while α is higher in the pre-pandemic period. The exceptions are the estimated coefficients α and β for S&P/TSX in Panels A and B, which show a reverse pattern. Therefore, no substantial differences were found in the evidence provided by both models, consistent with previous research (e.g. [22,53]). Since this model accounts for infinite persistence resulting in an unlikely explosive conditional variance, we then estimate an ARMA–FIGARCH(1, d, 1) process to account for an intermediate range of persistence, a more plausible hypothesis.

Table 4 provides the results for both pre-pandemic (Panel A) and during pandemic sub-periods (Panel B). Again, we find that except from the constant all coefficients in the variance equation are positive and highly significant. Consistent with previous evidence, past volatility has also a greater impact in the conditional variance in the COVID-19 period than in its pre-pandemic phase, as given by the coefficient-β estimates. This effect is more pronounced for FTSE/MIB and S&P/TSX, two of the most volatile indices (see, Table 1, Panel B), which exhibit a coefficient-β of 0.8929 and 0.74, respectively. In contrast, NIKKEI 225 is the least impacted index, exhibiting a coefficient-β of 0.3826.

As noted earlier one of the greatest innovations of this model, which constitutes its most appealing feature, is that it can measure the degree of persistence of shocks by allowing parameter d to vary between 0 and 1. Our results show that the G7’s volatility is highly persistent ranging from 0.1970 (FTSE/MIB) to 0.5814 (NIKKEI 225) in Panel A and from 0.22 (FTSE 100) to 0.929 (S&P 500) in Panel B and, therefore shocks to the volatility process tend to persist over time. As a consequence, the parameter restrictions d = 0 and d = 1 corresponding to the GARCH and IGARCH models are further rejected. Except from NIKKEI 225 and FTSE 100, all markets became more persistent with the COVID-19 outbreak. This is consistent with previous evidence, which suggests that crises tend to decline the rate at which shocks die out (see e.g. [19]). The explanation for this may lie in the fact that in highly uncertain scenarios dominated by market crashes, the effects of certain policies to promote financial recovery become delayed, due to market rigidities and the herding behavior of investors who tend to replicate previous strategies, thus prolonging similar patterns of behavior in stock markets [54–57]. In particular, in the case of COVID-19 outbreak, travel bans and lockdowns, which paralyzed whole economies for some time, seemed to be determinant for the persistence of market crises.

To check the adequacy of these models to describe the data, we computed a number of misspecification tests. The insignificance of the Ljung–Box statistics for all series and for all models confirms that the ARMA specifications adopted were sufficient to correct the serial correlation present in the data. Moreover, the insignificance of the ARCH-LM and the Ljung–Box statistics of the squared residuals also proves that the GARCH-type models adopted could capture this feature of the series.

Finally, to discriminate between models we employ the Log-Likelihood criterion as suggested by Sin and White [58]. Our results (Tables 2–4) show that the FIGARCH(1, d, 1) is the model that best captures the volatility dynamics. This is to be expected as this process was especially designed to describe persistent phenomenon and the parameter restrictions d = 0 and d = 1 corresponding to the GARCH and IGARCH models were already rejected.

4. Conclusions

In this paper, we investigated the volatility persistence of the G7’s main stock market indices over two distinct sub-samples: pre and during COVID-19 periods, in order to examine how markets reacted to the virus outbreak. To this end, we gathered data from March 4, 2019 to March 18, 2021 and divided the whole sample according to its breakpoints. We
Table 3
Estimates and diagnosis tests of the ARMA–IGARCH(1,1) model.

|                      | Mean equation | Variance equation | $L_L$ | Diagnosis tests |
|----------------------|---------------|-------------------|-------|-----------------
|                      | $c$ | $\psi_1$ | $\psi_2$ | $\theta_1$ | $\theta_2$ | $\omega$ | $\alpha$ | $\beta$ | Q-stat | ARCH-LM | $Q^2$-stat |
| **Panel A — Pre-pandemic period** | | | | | | | | | |
| S&P/TSX              | 0.1066 ** | 0.0423 ** | - | - | - | - | 0.0261 * | 0.6438 ** | 0.3562 ** | -151.467 | 45.7285 | 1.0739 | 9.9067 |
| CAC 40               | 0.0366 ** | -0.2218 ** | 0.2766 ** | 0.1212 ** | 0.2431 ** | -151.467 | 45.7285 | 1.0739 | 9.9067 |
| DAX 30               | 0.1306 ** | -0.2251 ** | - | 0.3039 ** | - | - | 376.085 | 39.4071 | 0.8791 | 19.0656 |
| FTSE MIB             | 0.0126 * | 0.0565 ** | - | - | - | - | 376.085 | 39.4071 | 0.8791 | 19.0656 |
| NIKKEI 225           | 0.1138 ** | 0.1644 ** | - | - | - | - | 376.085 | 39.4071 | 0.8791 | 19.0656 |
| FTSE 100             | 0.0405 ** | 0.0994 ** | - | 0.3708 ** | - | - | 376.085 | 39.4071 | 0.8791 | 19.0656 |
| S&P 500              | 0.0927 * | 0.2231 ** | - | 0.2107 ** | - | - | 376.085 | 39.4071 | 0.8791 | 19.0656 |
| **Panel B — During pandemic period** | | | | | | | | | |
| S&P/TSX              | 0.1200 * | -0.9521 ** | - | - | - | - | 21.76 ** | 0.7493 ** | 0.2507 ** | -360.91 | 27.7834 | 19.9359 | 1.2599 |
| CAC 40               | 0.0902 ** | 0.0181 ** | -0.2213 ** | 0.1956 * | 0.3176 ** | -360.91 | 27.7834 | 19.9359 | 1.2599 |
| DAX 30               | 0.1468 * | -0.2878 ** | - | 0.2821 ** | - | - | 38.0375 | 7.0099 | 21.3635 |
| FTSE MIB             | 0.1526 * | 0.5880 ** | - | - | - | - | 38.0375 | 7.0099 | 21.3635 |
| NIKKEI 225           | 0.1726 ** | -0.5934 ** | - | 0.6076 ** | - | - | 38.0375 | 7.0099 | 21.3635 |
| FTSE 100             | 0.0443 ** | 0.3991 ** | - | 0.6243 ** | - | - | 38.0375 | 7.0099 | 21.3635 |
| S&P 500              | 0.1327 ** | -0.2825 ** | - | 0.3808 ** | - | - | 38.0375 | 7.0099 | 21.3635 |

Notes: This table summarizes the results of the quasi-maximum likelihood estimation of the ARMA–IGARCH class model for the daily returns of the G7’s main stock market indices. $c$ and $\omega$ are the constant terms of the mean and variance equations, respectively. $\psi_1$ and $\psi_2$ are the parameters of the AR(1) and AR(2) autoregressive models, while $\theta_1$ and $\theta_2$ describes the parameters of the MA(1) and MA(2) moving average processes. $L_L$ is the Log-likelihood function. Q-stat represents the empirical statistics of the Ljung-Box test [41] up to 12 lags. ARCH-LM denotes the Engle [45] test for homoscedasticity up to 12 lags and $Q^2$-stat is the Ljung-Box statistics of the squared residuals [44] up to 12 lags.

**Indicates significance at 1% level.

*Indicates significance at 5% level.
Table 4: Estimates and diagnosis tests of the ARMA–FIGARCH(1,1) model.

|                  | Mean equation | Variance equation |            |            |            | Ll          | Diagnosis tests | Q-stat | ARCH-LM | Q^2-stat |
|------------------|---------------|-------------------|------------|------------|------------|-------------|----------------|---------|----------|----------|
|                  | c          | \( \varphi_1 \) | \( \varphi_2 \) | \( \theta_1 \) | \( \theta_2 \) | \( \omega \) | \( \alpha \) | \( \beta \) | \( d \) |          |
| Panel A – Pre-pandemic period |               |                   |           |           |           |             |                 |         |          |          |
| S&P/TSX          | 0.0487      | 0.6692            | *         | -         | -         | 1.5811 **  | 0.9532 **  | 0.6693 **  | 0.2642 **  | -73.75    | 17.0841   | 1.2698  | 13.9101   |
| CAC 40           | 0.1208      | 0.9909            | *         | 0.1053 ** | 0.0289 ** | 0.8445 **  | 0.0171 **  | 0.3345 **  | 0.4691 **  | -315.398  | 55.5389   | 0.5206  | 39.7614   |
| DAX 30           | 0.1537      | 0.6661            | *         | -         | 0.6771 ** | 1.3329 **  | 0.1029 **  | 0.2654 **  | 0.4790 **  | -361.926  | 45.7940   | 0.8888  | 40.6697   |
| FTSE MIB         | 0.1095      | 0.1171            | *         | -         | -         | 5.6458 **  | 0.9613 **  | 0.7790 **  | 0.1970 **  | -247.783  | 50.7541   | 0.1232  | 33.0669   |
| NIKKEI 225       | 0.0168      | 0.0636            | *         | -         | 0.0752 ** | 1.8118     | 0.4741      | 0.0171 **  | 0.3345 *   | -361.377  | 48.1956   | 1.3253  | 44.0321   |
| FTSE 100         | 0.0415      | 0.4401            | *         | -         | 0.1338 ** | 1.2416     | 0.0395 **  | 0.2983 **  | 0.5199 **  | -325.922  | 45.9402   | 1.1502  | 37.3779   |
| S&P 500          | 0.1259      | 0.1932            | *         | -         | 0.0566 ** | 2.5053     | 0.3879      | 0.0651 **  | 0.4639 **  | -257.987  | 52.5548   | 0.2378  | 32.9821   |

|                  |               |                   |           |           |           |             |                 |         |          |          |
| Panel B – During pandemic period |               |                   |           |           |           |             |                 |         |          |          |
| S&P/TSX          | 0.1423      | 0.1367            | *         | -         | -         | 21.0541 ** | 0.7417      | 0.7400 **  | 0.6409 **  | -225.106  | 20.1274   | 0.8981  | 21.3682   |
| CAC 40           | 0.0906      | 0.0545            | *         | 0.0031 ** | 0.1153 ** | 3.8756     | 0.1474 **   | 0.6740 **  | 0.6058 **  | -412.956  | 34.0580   | 0.5094  | 41.5711   |
| DAX 30           | 0.1519      | 0.1733            | *         | 0.1069 ** | -         | 3.5763     | 0.3672 **   | 0.6646 **  | 0.5143 **  | -420.668  | 43.0850   | 0.2090  | 44.3731   |
| FTSE MIB         | 0.1489      | 0.0051            | *         | -         | -         | 19.5453 ** | 0.4522 **   | 0.8092 **  | 0.8018 **  | -348.315  | 30.6073   | 0.7656  | 41.4490   |
| NIKKEI 225       | 0.1541      | 0.0779            | *         | -         | 0.0951 ** | 4.7782     | 0.1448 **   | 0.3826 **  | 0.4986 **  | -387.013  | 38.4874   | 0.5075  | 52.0713   |
| FTSE 100         | 0.0609      | 0.0612            | *         | 0.0150 ** | -         | 1.5054     | 0.0296 **   | 0.5459 **  | 0.2200 **  | -414.283  | 48.1959   | 0.5197  | 35.4462   |
| S&P 500          | 0.1480      | 0.0238            | *         | 0.0425 ** | -         | 0.0644     | 0.2323 **   | 0.4336 **  | 0.9290 **  | -404.641  | 41.9379   | 0.4399  | 27.7019   |

Notes: This table provides the results of the quasi-maximum likelihood estimation of the ARMA–FIGARCH class model for the daily returns of the G7’s main stock market indices. \( c \) and \( \omega \) refer to the constant terms of the mean and variance equations, respectively. \( \varphi_1 \) and \( \varphi_2 \) are the parameters of the AR(1) and AR(2) autoregressive models, whereas \( \theta_1 \) and \( \theta_2 \) denote the parameters of the MA(1) and MA(2) moving average processes. \( Ll \) represents the Log-likelihood function. Q-stat is the empirical statistics of the Ljung–Box test \([41]\) up to 12 lags. ARCH-LM denotes the Engle \([45]\) test for homoscedasticity up to 12 lags and \( Q^2 \)-stat stands for the Ljung–Box statistics of the squared residuals \([44]\) up to 12 lags.

*Indicates significance at 5% level.
observed that all series exhibited a structural break in a short time interval right after the declaration on March 11, 2020 of COVID-19 as a global pandemic by WHO (2020). We also found higher levels of volatility in the COVID-19 era, as expected. Then, we proceeded with the estimation of the GARCH, IGARCH and FIGARCH models in an effort to examine the type of memory each time series exhibit and how it differed across sub-periods. Our results showed that the coefficients $\beta$ in the three models were always greater in the COVID-19 sub-period. Moreover, the sum of coefficients $\alpha$ and $\beta$ in the GARCH model were very close to unity suggesting the adoption of an IGARCH process. We also found some similarities in the estimation results of both models, which is not surprising as the IGARCH accommodates the GARCH model, as a special case. Finally, the results of the FIGARCH model confirmed that all series exhibited persistence, yet of different intensity across sub-samples. Thus, while the pre-pandemic period displayed lower levels of persistence it has greatly increased with the outbreak of COVID-19 pandemic. For example, S&P 500 (0.929) and FTSE/MIB (0.8018) were the most persistent indices in contrast to FTSE 100 (0.22) and NIKKEI 225 (0.4986), which displayed lower levels of persistence during the COVID-19 sub-period. Market rigidities, the herding behavior of investors and the effects of lockdowns and travel bans might explain the tendency for shocks to die out slowly at this stage.

In short, four salient points have emerged from this research. First, is that the behavior of stock market prices in developed economies tend to vary over time. As a result, volatility itself is not stable thus evidencing clusters of different intensity. Second, these clusters, which resulted in higher levels of volatility and persistence after the pandemic outburst suggest the presence of regime shifts. Third, the persistent nature of volatility evidenced by the return series may imply predictability of returns and therefore past observations can be used to predict future returns, thus contradicting the weak form market efficiency hypothesis. Fourth, this may have consequences on the duration of market crisis, which may tend to endure giving rise to long lasting crisis.

Overall, our findings contributed to the existing literature on the effects of COVID-19 on financial markets because it focused on how this crisis affected market persistence, which to the best of our knowledge was not yet been examined before. Thus, it follows a recent strand in literature, which analyze the impact of health contingencies in the financial system and therefore alerts to the fact that stock markets may be affected not only by intrinsic financial factors, such as the herding behavior of investors or market rigidities, but also by external causes like a pandemic. Another positive aspect of this research is that it highlighted the importance of alternative methods based on econometric models to gauge the persistent nature of data in contrast to the traditional approach, which relied mainly on the Hurst exponents. Finally, the ultimate advance of this research was to demonstrate how stock market returns behave in turbulent environments. We hope that this may be of some use to bank regulators, risk managers and speculators, whom are struggling to minimize the impacts of this global pandemic.

CRediT authorship contribution statement

Sónia R. Bentes: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualization, Supervision, Project administration, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was funded by FCT, I.P. — the Portuguese national funding agency for science, research and technology, under the Project UIDB/04521/2020, by BRU — Business Research Unit (IBS, Lisbon, Portugal) and by Instituto Politécnico de Lisboa as part of the IPL/2020/FIN/ISCAL project, which we thankfully acknowledge.

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