The Persistence of Financial Volatility After COVID-19

Vera-Valdés, J. Eduardo

Published in:
Finance Research Letters

DOI (link to publication from Publisher):
10.1016/j.frl.2021.102056

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

Finance Research Letters 44 (2022) 102056

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

The persistence of financial volatility after COVID-19

J. Eduardo Vera-Valdés [a,b]

[a] Department of Mathematical Sciences, Aalborg University, Skjernvej 4A, Aalborg Øst 9210, Denmark
[b] CREATES, Denmark

ARTICLE INFO

JEL classification:
G01
G15
C22

Keywords:
COVID-19
Pandemic
Volatility
VIX
Realized variance
Persistence change

ABSTRACT

This paper analyzes the long-term effects of COVID-19 on financial volatility. We estimate the long memory parameters before and after COVID-19 for the VIX and realized variances for several international markets. Our results show that volatility measures for most countries experienced increases in the degrees of memory following the pandemic. Moreover, several volatility measures became nonstationary, signaling the start of a period with higher and more persistent financial volatility. We show that these changes in the degrees of memory are statistically significant using a test for change in persistence.

1. Introduction

The COVID-19 pandemic is one of the most severe health crises in recent memory. The official death toll worldwide surpassed 2 million as of January 15, 2021, four months after reaching 1 million on September 29, 2020. That is, the death toll of the first eight months of the pandemic was doubled in half the amount of time. Given reporting problems, the actual death toll may not be known for several years.

To slow the infection rate, countries around the world imposed restrictions on economic activity. The pandemic and the economic restrictions resulted in reductions in GDP and mass unemployment. In the US, GDP fell 11.2% from 2019Q4 to 2020Q2, while unemployment rose from 3.5% in February to 14.8% in April; see [12]. Similar drops in economic activity are reported worldwide. Moreover, the economic effects may be felt even in the long-run, see [24]. The authors show that shocks that originate in a pandemic-associated regime are more persistent than shocks in regular regimes. These long-term effects could explain the elevated unemployment rates over the next three years projected by The Congressional Budget Office and the Federal Reserve, see [12,27].

In the financial sector, one of the pandemic's immediate effects has been a substantial increase in volatility. [5] identifies the current pandemic as having the greatest impact on stock market volatility in the history of pandemics. The authors measured volatility using the Chicago Board Options Exchange (CBOE) Volatility Index (VIX). Their research identifies government limitations on commercial activity and restrictions on consumers as the reason for increased volatility. [29] finds similar results for 67 countries. Furthermore, [1] used the S&P 500 realized variance as a proxy for the financial markets' volatility and showed that it increases with data on new cases and deaths. Meanwhile, [4] and [16] show increases in risk for several industries after the pandemic, particularly in the travel and hospitality sectors.

It has been proven that volatility indexes show long memory, the statistical property that events in the past can be felt even after

E-mail address: eduardo@math.aau.dk.

https://doi.org/10.1016/j.frl.2021.102056
Received 31 January 2021; Received in revised form 24 March 2021; Accepted 6 April 2021
Available online 19 April 2021
1544-6123/

Table 1
Symbols for the VIX and the markets considered in this study.

AEX	AEX index	IXIC	Nasdaq 100
AORD	All Ordinaries	N225	Nikkei 225
BFX	Bell 20 Index	OMXC20	OMX Copenhagen 20 Index
BVLG	PSI All-Share Index	OMXHPI	OMX Helsinki All Share Index
BVSP	BVSP BOVESPA Index	OMXSPI	OMX Stockholm All Share Index
DJI	Dow Jones Industrial Average	RUT	Russel 2000
FCHI	CAC 40	SMSI	Madrid General Index
FTMIB	FTSE MIB	SPX	S&P 500 Index
FTSE	FTSE 100	STI	Straits Times Index
GDAXI	DAX	STOXX50E	EURO STOXX 50
IBEX	IBEX 35 Index	VIX	CBOE VIX

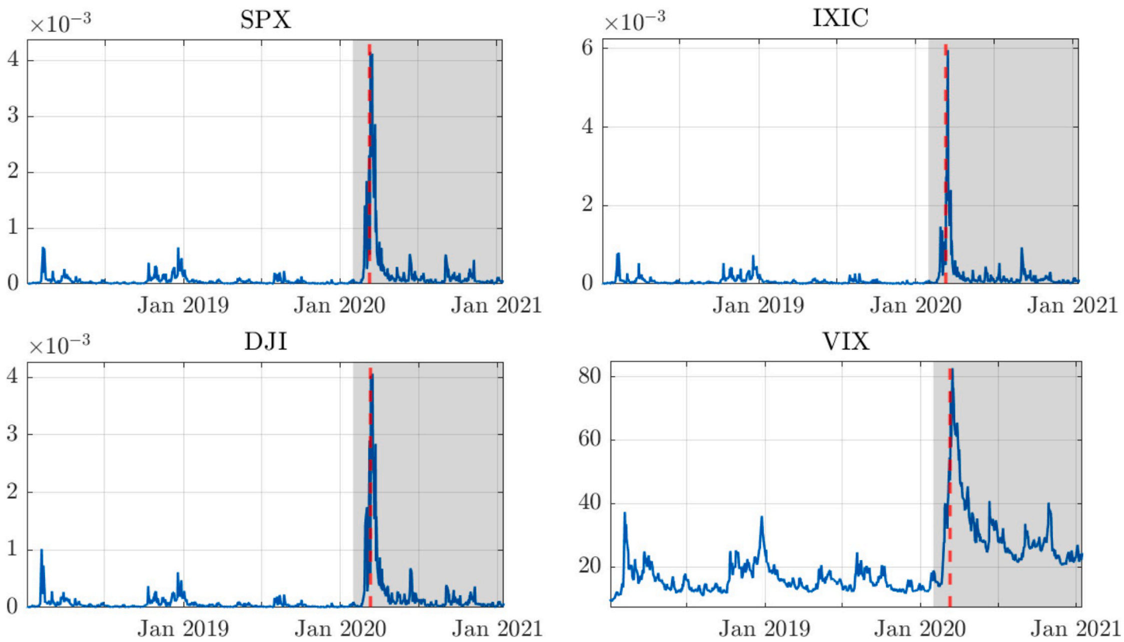

Fig. 1. Volatility indexes. The shaded area covers from the World Health Organization's declaration of a Public Health Emergency of International Concern. The vertical red line signals the formal declaration of a pandemic.

much time has passed; see, among others, [18,6,7,21]. Establishing the long memory properties of volatility helps understand the long-lasting effects of shocks. While the impact of new realizations is transitory for stationary series, new realizations have permanent effects for nonstationary cases. Thus, assessing the degree of memory of volatility indexes during and after the pandemic is of major interest.

Moreover, it has been shown that the level of memory of volatility indexes changes over time. [9] show that the degree of memory of the VIX's long memory parameter increased significantly during the 2007-2009 crisis in comparison to pre- (2004-2006) and post-crisis periods (2010-2016). The authors based their results on estimating the degree of memory in selected subsamples, but no formal test for change of persistence was conducted.

This paper contributes to the literature by characterizing the long memory properties of the most used volatility indexes during and after the pandemic. In particular, we test if the pandemic produced a change in the degree of memory of the VIX and realized variances for several international markets.

2. Data and methods

2.1. Volatility measures and COVID-19

We analyze the VIX and realized variances for several markets across the world. The VIX is commonly referred to as the "investor fear gauge" [28], while [3] argue that realized variance measures provide more information about volatility than GARCH-type models. The data was obtained from [13] and [14], and runs from January 1, 2018, to January 15, 2021. For our main analysis, we gather data on 21 realized variances for several international markets. The symbols for the VIX and the markets considered in this study are shown in Table 1. For the realized variance measures, we consider those computed using five-minute returns within a day, subsampled at a one-minute frequency, to avoid microstructure noise; see [2].

For illustrative purposes, Figure 1 shows the VIX and realized variance measures for the S&P 500 (SPX), the Nasdaq 100 (IXIC), and the Dow Jones Industrial Average (DJI).

On January 30, 2020, the World Health Organization's Director General declared that the COVID-19 outbreak constituted a Public Health Emergency of International Concern (PHEIC). In the figure, the shaded area covers from the PHEIC announcement to the end of the sample, while the red line signals the formal declaration of a pandemic on March 11, 2020. The figure shows that volatility measures already reached high values before the formal declaration of the pandemic. This signals to a financial sector reacting to the COVID-19 emergency well before the official pandemic declaration. [22] point to February 24, 2020, as the date that a change in investors' expectations regarding the effect of the shock affecting the financial channels took place. The authors denote this as the "fever period". We designate the PHEIC announcement as the start of the COVID subsample for our main analysis and consider the fever period in our robustness exercises. The PHEIC announcement date is considered exogenous to the financial sector, and it is thus selected to avoid endogeneity problems in the analysis.

As shown in the figure, volatility increased significantly in the period after the PHEIC announcement. The DJI, IXIC, and VIX reached their maximum on March 16, 2020. The SPX reached its maximum on March 12, 2020, with a comparable second-highest value on March 16, 2020. Similar behavior is observed for all volatility measures considered in this study.

2.2. Long memory

The time series literature has used the term long memory to indicate that the effects from previous disturbances take longer to dissipate than what standard models can capture. Long memory is typically described as an autocorrelation function that shows hyperbolic decay instead of the standard geometric one.

Let x_t be a series with long memory and $\gamma(k)$ be its autocorrelation function, then,

$$\gamma(k) \sim ck^{2d-1} \quad \text{as} \quad k \to \infty, \tag{1}$$

where c is a constant and $d \neq 0$ is the degree of memory. In the above, for $g(x) \neq 0$, $f(k) \sim g(x)$ as $k \to k_0$ denotes that $f(k)/g(k)$ converges to 1 as k tend to k_0. Note that the series will display long memory for $0 < d < 1$, which implies that disturbances have long-lasting repercussions. Moreover, the series is stationary for $d < 1/2$, and will revert to its mean for $d < 1$. Series with $d \geq 1$ are such that disturbances have permanent effects.

Estimation of the degree of memory is typically done in the frequency domain to circumvent the need to model the short memory dynamics. The estimators include the log-periodogram regression by [15] and [23]; and the exact local Whittle approach of [25]. The estimators evaluate the periodogram of the time series, an estimator of the spectral density, in a vicinity of the origin, where the spectral density is driven only by the memory parameter d.

Let $f_X(\lambda)$ be the spectral density of the long memory series x_t at frequency λ, then,

$$f_X(\lambda) \sim c\lambda^{-2d} \quad \text{as} \quad \lambda \to 0, \tag{2}$$

where c is a constant.

On the one hand, the log-periodogram regression [GPH, henceforth] is given by

$$\log(I(\lambda_k)) = c - 2d\log(\lambda_k) + u_k, \quad k = 1, \cdots, m, \tag{3}$$

where $I(\lambda_k)$ is the periodogram of x_t, $\lambda_k = e^{i2\pi k/T}$ are the Fourier frequencies, c is a constant, u_k is the error term, and m is a bandwidth parameter that grows with the sample size.

On the other hand, the exact local Whittle estimator [ELW, henceforth] minimizes the function

$$R(d) = \log\left(\frac{1}{m}\sum_{k=1}^{m} I_{\Delta^d}(\lambda_k)\right) - \frac{2d}{m}\sum_{k=1}^{m}\log(\lambda_k), \tag{4}$$

where $I_{\Delta^d}(\lambda_k)$ is the periodogram of $(1-L)^d x_t$, $\lambda_k = e^{i2\pi k/T}$ are the Fourier frequencies, and m is the bandwidth parameter that grows with the sample size. We use the standard binomial expansion to decompose $(1-L)^d$ in a series with hyperbolic decaying coefficients.

Note that the zero frequency is not included in both estimators, making them robust to the specification of the mean. Moreover, the estimators are consistent and asymptotically normal. For our analysis, we use the mean-squared error optimal bandwidth of $T^{4/5}$, where T is the sample size, obtained by [17].

2.3. Test for persistence change

Several tests have been proposed to determine if a time series shows changes in persistence. Most of the tests have focused on assessing a change from short memory to long memory or from unit root processes to stationary ones. Our analysis uses the test developed by [19] [MR, henceforth], capable of detecting changes between long memory processes with different memory parameters. The test is based on the recursive estimation of the [8] test, and it is capable of dealing with an unknown date of the change, trends, and

Table 2
Long memory estimates and change of persistence test statistics for volatility measures. The table shows estimates by the GPH and ELW methods and their standard errors, below between parentheses. The MR statistic is also shown for a test of no increase in the degree of memory, and the 99% critical value below between parentheses. Bandwidth of $T^{4/5}$. The 10%, 5%, and 1% levels of significance are denoted by *, **, and ***, respectively. †For the VIX, the 95% critical value is shown.

Volatility measures	Long memory estimates						Change persist. test
	Whole sample		Pre-COVID		COVID		
	01/Jan/2018-15/Jan/2021		01/Jan/2018-30/Jan/2020		31/Jan/2020-15/Jan/2021		
	GPH	ELW	GPH	ELW	GPH	ELW	MR
AEX	0.715***	0.703***	0.429***	0.459***	0.777***	0.746***	131.7***
	(0.048)	(0.035)	(0.057)	(0.041)	(0.082)	(0.056)	(10.2)
AORD	0.472***	0.488***	0.188***	0.252***	0.481***	0.514***	257.3***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.082)	(0.056)	(9.1)
BFX	0.717***	0.680***	0.416***	0.406***	0.683***	0.667***	367.5***
	(0.048)	(0.035)	(0.057)	(0.041)	(0.082)	(0.056)	(10.0)
BVLG	0.686***	0.687***	0.291***	0.370***	0.728***	0.731***	109.3***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(8.9)
BVSP	0.734***	0.705***	0.331***	0.347***	0.799***	0.792***	195.0***
	(0.050)	(0.036)	(0.058)	(0.041)	(0.085)	(0.057)	(8.6)
DJI	0.713***	0.674***	0.383***	0.441***	0.673***	0.698	31.4
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(10.5)
FCHI	0.679***	0.692***	0.347***	0.447***	0.669***	0.695***	505.3***
	(0.048)	(0.035)	(0.057)	(0.041)	(0.082)	(0.056)	(9.9)
FTMIB	0.684***	0.709***	0.517***	0.536***	0.759***	0.781***	56.3***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(9.1)
FTSE	0.438***	0.435***	0.200***	0.237***	0.307***	0.391***	30.0***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(8.9)
GDAXI	0.807***	0.834***	0.48***	0.493***	0.829***	0.831***	152.5***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(9.6)
IBEX	0.701***	0.674***	0.378***	0.447***	0.649***	0.627***	296.2***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.082)	(0.056)	(9.7)
IXIC	0.658***	0.692***	0.489***	0.501***	0.911***	0.887***	48.9***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(10.3)
N225	0.538***	0.565***	0.470***	0.487***	0.525***	0.545***	34.5***
	(0.050)	(0.036)	(0.059)	(0.042)	(0.085)	(0.057)	(11.4)
OMXC20	0.531***	0.525***	0.292***	0.254***	0.786***	0.786***	163.7***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(9.6)
OMXHPI	0.695***	0.699***	0.281***	0.307***	0.751***	0.767***	164.0***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(9.3)
OMXSPI	0.774***	0.800***	0.386***	0.442***	0.908***	0.885***	174.9***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(8.7)
RUT	0.965***	0.999***	0.441***	0.461***	0.942***	0.945***	90.6***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(9.2)
SMSI	0.764***	0.739***	0.424***	0.544***	0.719***	0.704***	96.9***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(9.5)
SPX	0.776***	0.788***	0.455***	0.501***	0.701***	0.716***	40.4***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(10.6)
STI	0.635***	0.671***	0.303***	0.308***	0.538***	0.574***	65.0***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(11.9)
STOXX50E	0.674***	0.632***	0.281***	0.378***	0.652***	0.661***	152.5***
	(0.048)	(0.035)	(0.057)	(0.041)	(0.083)	(0.056)	(9.6)
VIX	1.058***	1.064***	0.781***	0.867***	1.151***	1.082***	8.2**
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)	(5.7)†

serial correlation.

The MR test proceeds as follows, let x_t be the time series we want to test for a change in memory, and let $\tau \in [\Lambda_l, \Lambda_u]$ with $1 < \Lambda_l < \Lambda_u < T$, and T the sample size. To ease notation, we assume that the time series starts at $t = 1$ and thus T denotes both the last observation and the sample size. The test proceeds by recursively considering the auxiliary regression given by:

$$z_t = \phi(\tau) z^*_{t-1} + e_t, \quad t = 2, \cdots, [\tau T], \tag{5}$$

where $z_t = (1 - L)^{-d} x_t$, and $z^*_{t-1} = \sum_{j=1}^{t-1} j^{-1} x_{t-j}$. Intuitively, the j coefficient helps control the hyperbolic decay of long memory processes. The test statistic is constructed by the supreme of the squares of the t-statistics associated with $\phi(\tau)$ as we recursively move τ, and the analogous t-statistic associated with the auxiliary regression in the time-reversed series.

3. Results

3.1. Main results

Table 2 presents the results from the long memory estimates in the whole sample and the pre-COVID and COVID subsamples. Moreover, the table shows the statistic from the MR test of change of degree of memory.

We highlight some interesting findings.

First, the degree of memory of all volatility measures increased for the COVID subsample compared to the pre-COVID subsample. Moreover, the null of no change in persistence is rejected at the 1% level for all realized variance measures and the 5% level for the VIX.

Second, the degree of memory for almost all realized variance measures increased from the stationary range to the nonstationary range. The only exceptions being the FTSE realized variance that remained in the stationary range, and the FTMIB and N225, where the confidence intervals cross over to the other side of the 0.5 value.

Third, even though the degree of memory of the VIX seems to increase to the non-mean reverting range, the confidence intervals associated with the estimates intersect the mean-reverting range. In this sense, the degree of memory signals a slow reversion to the mean. This is in line with the VIX dynamics plotted in Figure 1.

Overall, our results show that the disturbances due to COVID-19 into financial volatility are more persistent than disturbances before the pandemic. This could relate to the fact that news related to the pandemic are typically evaluated in terms of their long-term effects on economic recovery. Expected future waves of contagions and vaccine developments are examples of news expected to impact the economy in medium to long horizons.

3.2. Robustness exercises

We estimate the long memory parameters with different values for the bandwidth parameter, dates for defining the COVID sample, and additional uncertainty measures as robustness exercises.

Table A.4 presents the results with a smaller bandwidth, while A.5 considers the start of the fever period on February 24, 2020 [22] to define the subsamples. The results from these robustness exercises, shown in Appendix A, broadly agree with our main results. They show that the degrees of memory of all volatility measures increased in the COVID subsample.

Furthermore, we consider conditional variance measures for several markets. We estimate GARCH and FIGARCH models on log-returns of several financial indexes; see [10] and [20]. The results, presented in Table A.3 in Appendix A, show that the conditional variances increase in persistence after the pandemic. Thus, they are in line with our main results.

Additional robustness exercises considering the COVID subsample to start at the official pandemic declaration, and data at different frequencies using ten-minute returns within a day, subsampled at every minute, show qualitatively similar results. They are not included in the present manuscript for space limitations, but they are available upon request.

3.3. Additional markets

It is important to note that not all international markets show a homogeneous response to the pandemic. Table B.7 in Appendix B presents the long memory estimates for 10 additional markets presented in Table B.6. The table shows that, among others, several Asian markets, the Norwegian, and the Swiss financial indexes showed much smaller changes in the degrees of memory. These results could relate to the role that trust in the government and society has on financial uncertainty during the pandemic. Trust is a significant factor in controlling the number of cases and deaths due to COVID-19, see [26]. In this regard, [11] show that a higher level of trust is associated with lower financial volatility, which could explain the smaller changes in degrees of memory. Similar results regarding international market volatility heterogeneity were reported by [20] and [30], particularly for Asian countries.

4. Conclusions

COVID-19 has been one of the most devastating health crises in the last several decades. The death toll is already in the millions, and it keeps increasing. In the economy, the pandemic brought decreases in growth and employment not observed since the great depression. In the financial sector, the health and economic shocks produced sharp rises in volatility measures worldwide.

This paper adds to the literature by assessing the long-term effects of the pandemic on financial volatility. We estimate the degrees of memory of dozens of volatility measures in subsamples before and after the pandemic. Our results show that, in addition to volatility measures achieving maximum levels during the pandemic, they became much more persistent. Most realized variances became nonstationary following the WHO's declaration of a Public Health Emergency of International Concern. Thus, our results suggest that the pandemic affects the financial sector even in the long run.

Overall, this paper supports the notion that the COVID-19 pandemic started a period of higher and more persistent financial volatility for several international markets. Our results are of interest to investors and asset managers, the higher level of persistence of volatility suggests an extended period of increased uncertainty that should be incorporated into trading strategies.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement: The data that support the findings of this study are publicly available at realized.oxford-man.ox.ac.uk and fred.stlouisfed.org/series/VIXCLS.

CRediT authorship contribution statement

J. Eduardo Vera-Valdés: Conceptualization, Methodology, Data curation, Formal analysis, Writing - original draft, Writing - review & editing, Visualization.

Declaration of Competing Interest

The authors declare no conflict of interest.

Acknowledgments

The authors thank the helpful comments and suggestions by the Referee. All errors remain those of the authors.

Appendix A. Robustness Exercises

Table A.3 presents the results from the robustness exercise analyzing the conditional variances of log returns. We consider GARCH and FIGARCH models for the conditional variances; see [20] and [10]. As detailed by the authors, the level of persistence for the conditional variance models are controlled by $\alpha+\beta$, and d, respectively.

Table A.4 presents the results from the robustness exercise with bandwidth given by $T^{1/2}$, where T is the sample size.

Table A.5 presents the results from the robustness exercise where the start of the COVID period coincides with the fever period. We use the $T^{4/5}$ bandwidth where T is the sample size.

Table A3

Persistence estimates for conditional variances. The table shows persistence estimates for the GARCH and FIGARCH models and their standard errors, below between parentheses. The 10%, 5%, and 1% levels of significance are denoted by *, **, and ***, respectively.

Volatility measures	Long memory estimates					
	Whole sample		Pre-COVID		COVID	
	01/Jan/2018-15/Jan/2021		01/Jan/2018-30/Jan/2020		30/Jan/2020-15/Jan/2021	
	GARCH $\alpha+\beta$	FIGARCH d	GARCH $\alpha+\beta$	FIGARCH d	GARCH $\alpha+\beta$	FIGARCH d
DJI	0.992***	0.566***	0.946***	0.235**	1.062***	0.453***
	(0.097)	(0.043)	(0.093)	(0.092)	(0.269)	(0.082)
SPX	1.002***	0.580***	0.974***	0.351***	1.019***	0.437***
	(0.089)	(0.037)	(0.088)	(0.117)	(0.218)	(0.081)
FTSE	0.956***	0.433***	0.743***	0.073	0.944***	0.246***
	(0.096)	(0.063)	(0.168)	(0.044)	(0.125)	(0.092)

Table A4

Long memory estimates and change of persistence test statistics for volatility measures. The table shows estimates by the GPH and ELW methods and their standard errors, below between parentheses. The MR statistic is also shown for a test of no increase in the degree of memory, and the 99% critical value below between parentheses. Bandwidth of $T^{1/2}$. The 10%, 5%, and 1% levels of significance are denoted by *, **, and ***, respectively. †For the VIX, the 95% critical value is shown.

Volatility measures	Long memory estimates						Change persist. test
	Whole sample		Pre-COVID		COVID		
	01/Jan/2018-15/Jan/2021		01/Jan/2018-30/Jan/2020		31/Jan/2020-15/Jan/2021		
	GPH	ELW	GPH	ELW	GPH	ELW	MR
AEX	0.288*	0.282***	0.231	0.321***	0.562**	0.572***	316***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(9.7)
AORD	0.36**	0.356***	0.055	0.15	0.779***	0.783***	257.3***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(9.1)
BFX	0.365**	0.348***	0.354**	0.404***	0.726***	0.719***	1029***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(9.9)
BVLG	0.323**	0.326***	0.03	0.406***	0.607***	0.611***	388.8***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.2)
BVSP	0.321**	0.338***	0.298*	0.402***	0.589***	0.571***	303.3***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.1)
DJI	0.323**	0.325***	0.186	0.36***	0.761***	0.763***	122.1***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(9.7)
FCHI	0.322**	0.312***	0.259	0.367***	0.565**	0.563***	1363.9***

(continued on next page)

Table A4 (*continued*)

Volatility measures	Long memory estimates						Change persist. test
	Whole sample		Pre-COVID		COVID		
	01/Jan/2018-15/Jan/2021		01/Jan/2018-30/Jan/2020		31/Jan/2020-15/Jan/2021		
	(0.15)	(0.096)	(0.166)	(0.104)	(0.22)	(0.129)	(10.0)
FTMIB	0.342**	0.336***	0.321**	0.296***	0.688***	0.699***	287.4***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.2)
FTSE	0.406***	0.394***	0.11	0.194*	0.853***	0.851***	30***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(8.9)
GDAXI	0.333**	0.322***	0.11	0.297***	0.646***	0.658***	463.2***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.2)
IBEX	0.339**	0.318***	0.075	0.092	0.484**	0.469***	635.9***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.1)
IXIC	0.289*	0.276***	0.362**	0.39***	0.511**	0.517***	244.1***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(9.5)
N225	0.326**	0.338***	0.314*	0.294***	0.555**	0.544***	70***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(8.9)
OMXC20	0.308**	0.315***	0.355**	0.449***	0.522**	0.506***	64.4***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.1)
OMXHPI	0.385**	0.368***	0.151	0.269***	0.763***	0.771***	302.6***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.2)
OMXSPI	0.357**	0.346***	0.135	0.26**	0.698***	0.709***	809.4***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.2)
RUT	0.314**	0.306***	0.497***	0.508***	0.519**	0.498***	283.2***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.2)
SMSI	0.317**	0.299***	-0.05	0.052	0.621***	0.626***	290.2***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(10.2)
SPX	0.319**	0.32***	0.306*	0.378***	0.698***	0.716***	72.7***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(9.6)
STI	0.353**	0.345***	0.184	0.318***	0.854***	0.843***	93.5***
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(9.0)
STOXX50E	0.293*	0.285***	0.145	0.304***	0.608***	0.61***	86.9***
	(0.15)	(0.096)	(0.166)	(0.104)	(0.22)	(0.129)	(10.2)
VIX	0.764***	0.694***	0.384**	0.541***	1.086***	1.144***	8.2**
	(0.15)	(0.096)	(0.17)	(0.107)	(0.22)	(0.129)	(5.7)†

Table A5

Long memory estimates and change of persistence test statistics for volatility measures. The table shows estimates by the GPH and ELW methods and their standard errors, below between parentheses. Bandwidth of $T^{4/5}$. The 10%, 5%, and 1% levels of significance are denoted by *, **, and ***, respectively.

Volatility measures	Long memory estimates					
	Whole sample 01/Jan/2018-15/Jan/2021		Pre-COVID 01/Jan/2018-24/Feb/2020		COVID 25/Feb/2020-15/Jan/2021	
	GPH	ELW	GPH	ELW	GPH	ELW
AEX	0.715***	0.703***	0.457***	0.457***	0.772***	0.731***
	(0.048)	(0.035)	(0.057)	(0.040)	(0.085)	(0.057)
AORD	0.472***	0.488***	0.191***	0.238***	0.487***	0.504***
	(0.049)	(0.035)	(0.057)	(0.040)	(0.085)	(0.057)
BFX	0.717***	0.680***	0.411***	0.406***	0.684***	0.641***
	(0.048)	(0.035)	(0.057)	(0.040)	(0.085)	(0.057)
BVLG	0.686***	0.687***	0.308***	0.382***	0.730***	0.722***
	(0.049)	(0.035)	(0.057)	(0.040)	(0.085)	(0.057)
BVSP	0.734***	0.705***	0.334***	0.347***	0.813***	0.797***
	(0.050)	(0.036)	(0.058)	(0.041)	(0.088)	(0.059)
DJI	0.713***	0.674***	0.423***	0.442***	0.674***	0.689***
	(0.049)	(0.035)	(0.057)	(0.041)	(0.086)	(0.058)
FCHI	0.679***	0.692***	0.419***	0.447***	0.667***	0.679***
	(0.048)	(0.035)	(0.057)	(0.040)	(0.085)	(0.057)
FTMIB	0.684***	0.709***	0.491***	0.537***	0.746***	0.767***
	(0.049)	(0.035)	(0.057)	(0.040)	(0.086)	(0.058)
FTSE	0.438***	0.435***	0.180***	0.212***	0.284***	0.383***
	(0.049)	(0.035)	(0.057)	(0.040)	(0.085)	(0.057)
GDAXI	0.807***	0.834***	0.432***	0.502***	0.827***	0.810***
	(0.049)	(0.035)	(0.057)	(0.040)	(0.086)	(0.058)
IBEX	0.701***	0.674***	0.422***	0.452***	0.658***	0.603***
	(0.049)	(0.035)	(0.057)	(0.040)	(0.085)	(0.057)

(*continued on next page*)

Table A5 (*continued*)

IXIC	0.658***	0.692***	0.450***	0.510***	0.921***	0.890***
	(0.049)	(0.035)	(0.057)	(0.041)	(0.085)	(0.057)
N225	0.538***	0.565***	0.449***	0.490***	0.522***	0.540***
	(0.050)	(0.036)	(0.058)	(0.041)	(0.087)	(0.059)
OMXC20	0.531***	0.525***	0.258***	0.250***	0.808***	0.781***
	(0.049)	(0.035)	(0.057)	(0.041)	(0.086)	(0.058)
OMXHPI	0.695***	0.699***	0.245***	0.268***	0.753***	0.758***
	(0.049)	(0.035)	(0.057)	(0.041)	(0.086)	(0.058)
OMXSPI	0.774***	0.800***	0.357***	0.395***	0.871***	0.865***
	(0.049)	(0.035)	(0.057)	(0.041)	(0.086)	(0.058)
RUT	0.965***	0.999***	0.431***	0.465***	0.957***	0.932***
	(0.049)	(0.035)	(0.057)	(0.041)	(0.085)	(0.057)
SMSI	0.764***	0.739***	0.434***	0.528***	0.690***	0.670***
	(0.049)	(0.035)	(0.057)	(0.040)	(0.085)	(0.057)
SPX	0.776***	0.788***	0.461***	0.501***	0.704***	0.708***
	(0.049)	(0.035)	(0.057)	(0.041)	(0.086)	(0.058)
STI	0.635***	0.671***	0.285***	0.309***	0.528***	0.551***
	(0.049)	(0.035)	(0.057)	(0.041)	(0.086)	(0.058)
STOXX50E	0.674***	0.632***	0.295***	0.346***	0.652***	0.648***
	(0.048)	(0.035)	(0.056)	(0.040)	(0.085)	(0.057)
VIX	1.058***	1.064***	0.719***	0.865***	1.096***	1.017***
	(0.049)	(0.035)	(0.057)	(0.040)	(0.085)	(0.057)

Appendix B. Additional Markets

Table B6
Symbols for the additional markets considered in this study.

BSESN	S&P BSE Sensex	MXX	IPC Mexico
GSPTSE	S&P/TSX Composite index	NSEI	NIFTY 50
HSI	HANG SENG Index	OSEAX	Oslo Exchange All-share Index
KS11	Korea Composite Index	SSEC	Shanghai Composite Index
KSE	Karachi SE 100 Index	SSMI	Swiss Stock Market Index

Table B7
Long memory estimates and change of persistence test statistics for volatility measures. The table shows estimates by the GPH and ELW methods and their standard errors, below between parentheses. The MR statistic is also shown for a test of no increase in the degree of memory, and the 99% critical value below between parentheses. Bandwidth of $T^{4/5}$. The 10%, 5%, and 1% levels of significance are denoted by *, **, and ***, respectively.

Volatility	Long memory estimates					
measures	Whole sample		Pre-COVID		COVID	
	01/Jan/2018-15/Jan/2021		01/Jan/2018-24/Feb/2020		25/Feb/2020-15/Jan/2021	
	GPH	ELW	GPH	ELW	GPH	ELW
BSESN	0.355***	0.393***	0.283***	0.316***	0.301***	0.375***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)
GSPTSE	0.735***	0.654***	0.459***	0.502***	0.521***	0.465***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)
HSI	0.334***	0.349***	0.406***	0.432***	0.277***	0.309***
	(0.049)	(0.036)	(0.059)	(0.042)	(0.084)	(0.057)
KS11	0.559***	0.485***	0.523***	0.599***	0.564***	0.524***
	(0.049)	(0.036)	(0.059)	(0.042)	(0.083)	(0.056)
KSE	0.496***	0.457***	0.277***	0.344***	0.431***	0.441***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)
MXX	0.348***	0.382***	0.242***	0.303***	0.348***	0.376***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)
NSEI	0.315***	0.350***	0.273***	0.317***	0.251***	0.325***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)
OSEAX	0.200***	0.230***	0.163***	0.217***	0.147***	0.216***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.084)	(0.057)
SSEC	0.535***	0.554***	0.503***	0.510***	0.483***	0.552***
	(0.050)	(0.036)	(0.059)	(0.042)	(0.083)	(0.056)
SSMI	0.630***	0.558***	0.424***	0.538***	0.442***	0.468***
	(0.049)	(0.035)	(0.058)	(0.041)	(0.083)	(0.056)

References

[1] Albulescu, C.T., 2020. COVID-19 and the United States financial markets' volatility. Finance Research Letters 38 (March 2020), 101699. https://doi.org/10.1016/j.frl.2020.101699.
[2] Andersen, T.G., Bollerslev, T., Diebold, F.X., Ebens, H., 2001. The distribution of realized stock return volatility. Journal of Financial Economics 61 (1), 43–76. https://doi.org/10.1016/S0304-405X(01)00055-1.
[3] Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2003. Modeling and forecasting realized volatility. Econometrica 71 (2), 579–625. https://doi.org/10.1111/1468-0262.00418.
[4] Baek, S., Mohanty, S.K., Glambosky, M., 2020. COVID-19 and stock market volatility: An industry level analysis. Finance Research Letters 37 (September), 101748. https://doi.org/10.1016/j.frl.2020.101748.
[5] Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M., Viratyosin, T., 2020. The unprecedented stock market reaction to COVID-19. Review of Asset Pricing Studies 10 (4), 742–758. https://doi.org/10.1093/rapstu/raaa008.
[6] Bandi, F.M., Perron, B., 2006. Long memory and the relation between implied and realized volatility. Journal of Financial Econometrics 4 (4), 636–670. https://doi.org/10.1093/jjfinec/nbl003.
[7] Bollerslev, T., Osterrieder, D., Sizova, N., Tauchen, G., 2013. Risk and return: Long-run relations, fractional cointegration, and return predictability. Journal of Financial Economics 108 (2), 409–424. https://doi.org/10.1016/j.jfineco.2013.01.002.
[8] Breitung, J., Hassler, U., 2002. Inference on the cointegration rank in fractionally integrated processes. Journal of Econometrics 110 (2), 167–185. https://doi.org/10.1016/S0304-4076(02)00091-X.
[9] Caporale, G.M., Gil-Alana, L., Plastun, A., 2018. Is market fear persistent? A long-memory analysis. Finance Research Letters 27 (January), 140–147. https://doi.org/10.1016/j.frl.2018.02.007.
[10] Chen, Z., Daigler, R.T., Parhizgari, A.M., 2006. Persistence of volatility in futures markets. Journal of Futures Markets 26 (6), 571–594. https://doi.org/10.1002/fut.20210.
[11] Engelhardt, N., Krause, M., Neukirchen, D., Posch, P.N., 2020. Trust and stock market volatility during the COVID-19 crisis. Finance Research Letters 38 (November 2020), 101873. https://doi.org/10.1016/j.frl.2020.101873.
[12] Falk, G., Carter, J., Nicchitta, I., Nyhof, E., Romero, P., 2021. Unemployment Rates During the COVID-19 Pandemic: In Brief. Congressional Research Service R46554, 1–13.
[13] FRED Federal Reserve Bank of St. Louis, 2021. Chicago Board Options Exchange, CBOE Volatility Index: VIX. https://fred.stlouisfed.org/series/VIXCLS.
[14] Gerd, H., Lunde, A., Shephard, N., Sheppard, K., 2009. Oxford-Man Institute's realized library. https://realized.oxford-man.ox.ac.uk/.
[15] Geweke, J., Porter-Hudak, S., 1983. The Estimation and Application of Long Memory Time Series Models. Journal of Time Series Analysis 4 (4), 221–238. https://doi.org/10.1111/j.1467-9892.1983.tb00371.x.
[16] Haroon, O., Rizvi, S.A.R., 2020. COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. Journal of Behavioral and Experimental Finance 27, 100343. https://doi.org/10.1016/j.jbef.2020.100343.
[17] Hurvich, C.M., Deo, R., Brodsky, J., 1998. The Mean Squared Error of Geweke and Porter-Hudak's Estimator of the Memory Parameter of a Long-Memory Time Series. Journal of Time Series Analysis 19 (1), 19–46. https://doi.org/10.1111/1467-9892.00075.
[18] Koopman, S.J., Jungbacker, B., Hol, E., 2005. Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. Journal of Empirical Finance 12 (3), 445–475. https://doi.org/10.1016/j.jempfin.2004.04.009.
[19] Martins, L.F., Rodrigues, P.M., 2014. Testing for persistence change in fractionally integrated models: An application to world inflation rates. Computational Statistics and Data Analysis 76, 502–522. https://doi.org/10.1016/j.csda.2012.07.021.
[20] Nguyen, D.T., Phan, D.H.B., Ming, T.C., Nguyen, V.K.L., 2021. An assessment of how COVID-19 changed the global equity market. Economic Analysis and Policy 69, 480–491. https://doi.org/10.1016/j.eap.2021.01.003.
[21] Osterrieder, D., Ventosa-Santaulària, D., Vera-Valdés, J.E., 2019. The VIX, the Variance Premium, and Expected Returns*. Journal of Financial Econometrics 17 (4), 517–558. https://doi.org/10.1093/jjfinec/nby008.
[22] Ramelli, S., Wagner, A.F., 2020. Feverish stock price reactions to COVID-19. Review of Corporate Finance Studies 9 (3), 622–655. https://doi.org/10.1093/rcfs/cfaa012.
[23] Robinson, P.M., 1995. Log-Periodogram Regression of Time Series with Long Range Dependence. The Annals of Statistics 23 (3), 1048–1072. https://doi.org/10.1214/aos/1176324636.
[24] Rodríguez-Caballero, C.V., Vera-Valdés, J.E., 2020. Long-lasting economic effects of pandemics: Evidence on growth and unemployment. Econometrics 8 (37), 1–16. https://doi.org/10.3390/econometrics8030037.
[25] Shimotsu, K., Phillips, P.C.B., 2005. Exact local Whittle estimation of fractional integration. The Annals of Statistics 33 (4), 1890–1933. https://doi.org/10.1214/009053605000000309.
[26] Vera-Valdés, J.E., 2021. The political risk factors of COVID-19. International Review of Applied Economics 35 (2), 269–287. https://doi.org/10.1080/02692171.2020.1866973.
[27] Weinstock, L.R., 2020. COVID-19: How Quickly Will Unemployment Recover? Congressional Research Service IN11460, 1–4.https://crsreports.congress.gov/product/pdf/IN/IN11460
[28] Whaley, R.E., 2000. The Investor Fear Gauge. The Journal of Portfolio Management 26 (3), 12–17. https://doi.org/10.3905/jpm.2000.319728.
[29] Zaremba, A., Kizys, R., Aharon, D.Y., Demir, E., 2020. Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe. Finance Research Letters 35 (April), 101597. https://doi.org/10.1016/j.frl.2020.101597.
[30] Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Finance Research Letters 36 (March), 101528. https://doi.org/10.1016/j.frl.2020.101528.