MEASURING ASYMMETRIC VOLATILITY OF UK, FRANCE, AND GERMAN STOCK MARKETS

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Abstract
The recent global pandemic impacted stock markets worldwide, including developed and emerging markets. This paper investigates changes in volatility from a sample of daily returns ofFTSE100, DAX and CAC for the UK, Germany, and France, respectively. We test the fitness of GARCH (1, 1) to model the volatility, measure the interrelationship between selected samples, and abstract the changes in volatility before and during the pandemic period. Used and analysed daily closing returns from 2000-01-01 to 2022-31-01 with Generalised Autoregressive Conditional Heteroskedasticity (GARCH 1, 1) and Value-at-Risk (VaR) with Normal and Mills approach. Data has been divided into three phases-before, during, and after the Covid 19 pandemic. The finding confirms persistent volatility for selected samples, the strong interrelationship among the German stock market and UK stock market than in France and German markets, dynamic changes in volatility patterns before, during and after the pandemic. The study results confirm the increase in normal volatility patterns after the pandemic. Further, finding exhibits the dynamics of volatility and response during the different four-phases, changing the degree of risk and prospective returns.

Keywords: *GARCH, European stock market, asymmetric volatility, COVID-19 pandemic, risk, stock returns*

Classification JEL: C32, C53, D53, G15, G17

1. INTRODUCTION

Understanding and forecasting volatility parameters have always been an area of curiosity, research and interest to investors' community, academicians, and researchers. It helps to add super values in future decision makings with two reasons. First, the generalised volatility pattern over a period testified with another period to determine the parametric changes in the volatility pattern. Second, changing phases of volatility interpret the possibility for the involvement of risk and prospective returns. The volatility in developed markets is lower than in developing and emerging markets worldwide. However, even established markets have been severely damaged by the COVID-19 pandemic. In this study, an attempt has been made to study the changes in the market movement pattern of developed stock markets. To model this object, we used a sample of the FTSE100 stock market in the United Kingdom, the DAX stock market in Germany, and the CAC stock market in France. We used econometric models like Autoregressive Conditional Heteroskedasticity (ARCH) and the Generalised Conditional Heteroskedasticity (GARCH) family to measure volatility estimators.Using selective econometric asymmetric modeling along with the Value at Risk in composition with DV and VFP, the paper attempts to capture the relative changes in asymmetric property with the impact on DV and VFP for UK, France and German stock markets.

During the pandemic period, when most countries were on lockdown due to the global epidemic of COVID-19 or Coronavirus pandemic, investors worldwide saw a significant drop in stock market prices. The uncertainty of such an incident increased the stock market's stress level. Such events directly impact stock market volatility behaviour patterns, and it is possible to abstract changes in volatility behaviour of developed stock markets using historical data from previous events. As a result, we divide the data into three phases, sampling volatility individually for the entire year prior to the COVID-19 pandemic, the entire year during the pandemic, and phase three, which includes the post-pandemic period.

This study examines the changes in volatility for developed European stock markets prior to, during, and after the pandemic.The stock market generally creates an abnormal slop during global events such as the pandemic of COVID-19 pandemic. Therefore the returns it is important to describe the time-varying conditional distribution based on heavy-tailed mixture models such as GARCH and Value at Risk(Nikolaev et al., 2013). It is important to understand the involvement of risk and the possibility for returns (Prasetya et al., 2018) suggests that investment in the stock market generates returns accompanied by associated investment degree of risk. Value at risk is considered the best model instrument to ascertain and analyse risk management parameters associated with the investments.

This paper objected to explore the information and complex stylized facts based on the relationship of degree of changes in the asymmetry and the impact on DV and VFP. Thus, the paper attempts to capture and explore the information which adds valuable contribution that supports researcher, readers and market-practitioner for better decision-making. In general, volatility considered as natural phenomenon of the stock markets, with the different degree of magnitude and impact. Further, in extra-ordinary time such as global events and pandemic period all stock markets have different response. Scholars across the world explored the reactions and response of the stock market considering the different events, programs, political events, pandemic events, global financial crisis etc. which provides strong and significant outcome that supported extensively to understand the movement pattern of the stock indices. However, stock market also captures the response from major events such as winning the cricket world cup, FIFA world cup or declaration of organizing the world sports and athletic events see (Gopane & Mmotla, 2019).

2. Literature Review

This section has provided detailed insights on various aspects of stock and commodity market volatility and various GARCH family models and VaR that capture the asymmetric volatility. Moreover, some important studies related to market volatility and COVID-19 pandemic that have been conducted recently are also mentioned. This section also deals with the various implications of existing studies which are applied to this study.

Volatility dynamics provides information about the spill-over, volatility clusters and presence of leverage effects, degree of persistent etc. that supports understanding the hidden parametric in the series returns. Eventually, the idea is to explore the hidden information behind the price movements of the indices or stocks, which captures all available information in daily price movements. For instance, (Rabbani et al., 2022; Jebran & Iqbal, 2016) examined the spill-over effect between the stock market and the forex exchange markets using the asymmetric GARCH models.Whereas, (Liu, 2020) used asymmetric models to capture the effect of COVID-19 pandemic on Chinese stock market relatively with Chinese composite index and sector indices finding how stock market responded to major volatility shocks. Therefore, the variation in daily variance remains as the important property for the interpretation and analysis.The daily variance gives evidence of risk associated with yesterday's investment value. Therefore, estimating intra-day volatility (daily volatility) is vital for a comprehensive view (Spulbar et al., 2022; Banerjee & Paul, 2020). The realisedgeneralised autoregressive conditional heteroskedasticity (GARCH) model beats standard GARCH models forecasting stock market volatility (Pintari&Subekti, 2018).Nonetheless, the GARCH class models (symmetric GARCH) explores the relative changes in volatility parameter and remained superior in understanding the level of persistent in volatility even with the study on single stock market (Spulbar et al., 2022; Osagie et al., 2020).

The semi-parametric model works uniformly well when examining the within-sample VaRs of a collection of stock market returns, and surprisingly, the distribution of sample identified to have a far more significant impact on the VaR estimates' performance than the specific parametric specification used for the GARCH modelequations(Rombouts & Verbeek, 2009). Many researchers used the Value at Risk model with GARCH (1, 1) modelto model the extreme value of volatility, risk, and probable returns. For instance, (Sowdagur & Narsoo, 2017; Füss et al., 2007) and also used to modest the bias for the parametric computation of volatility (Haddad & Hasanzade, 2020).Pourmansouri et al. (2022) examined the behaviour of another emerging stock market, such as Iran based on the linkage between corporate governance efficiency and major shareholders' decissions during COVID-19 pandemic, both before and after this period.

A study regressed the effects of capital adequacy, credit losses and efficiency ratio on return on assets and return on equity of Indian banks during the COVID-19 pandemic (Hawaldar, Meher, Kumari, & Kumar, 2022). Hawaldar (2016) and Iqbal (2015) tested cross sectional verification of portfolio returns. Iqbal (2014) and Iqbal, Mallikarjunappa & Nayak (2007) found out the earning announcement affects stock returns and stock market is not efficient in semi strong form of efficient market hypothesis. The findings of Spulbar et al. (2022)confirmed the presence of the leverage effect during the sample period in Japan stock market. The empirical results identified the presence of high volatility in Japan stock market during COVID-19 pandemic.Also (Kumar et al., 2021) used GARCH and EGARCH models to examine the response of stock market against the pandemic period considering the samples of BRICS nations suggesting the different response of stock market during the same period.

Under varied market conditions, evaluating changes in volatility using a sample of developed European stock markets will report changes in volatility dynamics to proper capitalisation.This has been a topic of interest in financial risk management, and the results based on univariate GARCH and VaR, which calculates the volatility parameters, are now garnering greater attention(Elenjical et al., 2016). Again, a study showing the impact of the pandemic on the asymmetric volatility of crude oil and natural gas prices listed in MCX of India using the EGARCH model (Meher, Hawaldar, Mohapatra, & Sarea, 2020). Similarly, a recent study depicts the leverage effect of COVID-19 pandemicon the stock price volatility of energy companies in India using GJR-GARCH and EGARCH models with high-frequency data(Meher, Hawaldar, Gil, & Dum, 2021). We compare periods in which market conditions suffer a shift in the volatility parameter with new alterations in daily volatility and annualised volatility.Badarla et al. (2022) investigated the behaviour of stock markets of Switzerland, Austria, China and Hong Kong using GARCH family models during COVID-19 pandemic.

Market risk is a financial risk associated with the stock market typically produced by price volatility and is closely linked to global news and financial markets. Value at Risk (VaR) is a determinant of market risk, defined as the highest loss achievable within a particular time horizon and at a given level of reliability(Jeřábek, 2020). Furthermore, a paper attempted to analyse the impact of ESG scores on the return and volatility of companies under NIFTY50(Meher, Hawaldar, Mohapatra, Spulbar, & Birau, 2020). A GARCH specification addresses abnormality of distributions and captures the heteroskedasticity, heavy tails – leptokurtic and volatility clustering (Deng, 2013). The choice of model aids in abstracting the best possible outcome dynamics, such as the efficiency of value-at-risk (VaR) backtests in the model or the choice of symmetric (GARCH) with VaR, which represented skewed and non-skewed distributions and incorporated advances in the stock market indexes(Tay et al., 2020). (Altun, 2020)suggests that when compared to normal and generalised error distributions, the GARCH model under TSLx considers innovation in distributions. The tests also assess the accuracy of VaR projections.Whether implied volatility or historic volatility Value-at-Risk models along with asymmetric EGARCH or normal GJR-GARCH models evident as the superior estimators to explore the asymmetric information see (Bams et al., 2017).

On the daily closing sample of the FSTE100, DAX, and CAC stock market indices, we also utilise the theory to estimate the risk parameter that provides more accurate statistics to examine GARCH volatility features, as well as changes in daily and annualised volatility, using the Value-at-Risk model(Tabasi et al., 2019). This work focuses on modelling and forecasting volatility. Moreover, it is also an attempt to understand the interrelationship between the movement of selected samples and abstract the changes in volatility during the global pandemic. During the COVID-19 pandemic, indices worldwide escalated the normal volatility range and modeled the behaviour of the European developed stock market. We consider the following stock indices, such as: FTSE100 - the UK, DAX - Germany and CAC –France.

3. Research methodology

Data related to daily closing indices from 01-01-2000 to 31-01-2022 have been extracted from Bloombergto capture changes, volatility clusters, the fitness of econometric models, and changes in volatility patterns. The study employed a sample of 5760 daily observations (daily closing prices) for the UKX, DAX and CAC indices, respectively. To abstract the volatility pattern changes, we partition the data into four phases for the computation of Value-at-Risk;Phase I – All three European sample markets was analysed during the entire study period (01-01-2000 to 31-01-2022), comprising 5760 daily OBS. Period II — A total of 261 daily OBS were counted from January 1, 2019, to December 31, 2019; phase III — Throughout the COVID-19 pandemic, a total of 262 daily OBS were counted, and Phase IV — After the COVID-19 phase, a total of 282 daily OBS were counted from January 1, 2021, to January 31, 2022.

For the conversion of series returns to log returns, the paper explores a formula:

$$r_t = ln\left(\frac{p_t}{p_{t-1}}\right) = ln(p_t) - ln(p_{t-1}). \qquad (1)$$

Where ln, indicates the natural logarithm function, total return of R at time *t. = r1+r2+r3+2…+rt – 1 +rt* which equivalent to R = *Ln (P1 / P0) + ... Ln (Pt-1 / Pt-2) + Ln (Pt / Pt-1).*

Augmented Dickey-Fuller (ADF) regression process is managed by:

$$\Delta y_t = c + \beta \cdot t + \delta \cdot y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \varepsilon_t. \qquad (2)$$

Where *y (t – 1)* indicates the first lag of the returns and $\Delta y(t-1)$ represents the first difference of series at the time (t-1).Moreover, the ADF process is applied as follows:

$$(1 - L)y_t = \beta_0 + (\alpha - 1)y_t - 1 + \varepsilon_i. \quad (3)$$

Further, the symmetric GARCH (1, 1) model is applied as:

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}, \quad (4)$$

where the distribution of mean property is the following equation:

$$ht = \mu + \varepsilon t. \quad (5)$$

The variance equation is calculated by:

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 \quad (6)$$

The first subscript in the GARCH concept denotes the order of *y2* terms on the right side, whereas the second subscript denotes the order of σ^2 terms. The y_t series = $y_t^2$and statistically becomes (AR) term due to the procedure, which imposes specific constraints on the coefficients. The model considers the values of past squared observations and past variances to model variance at the time (t), resulting in the properties of the mean equation and variance equation indicated in formulas (5) and (6), respectively (6). The white-noise process (t) describes the white noise that is dispersed independently and identically with expectations between (0) and (1). Additionally, as a process to conditional variance, which is represented by (σ_t^2)and can be anticipated using (r_{t-1}^2).

Therefore, (h_t) represents the degree of constant, which is denoted by (ω), the ARCH term ($\alpha_1 u_{t-1}^2$) and the GARCH term ($\beta_1 h_{t-1}$).

To measure the Value-at-Risk during the different phases, we consider the log difference of selected stock market indexes for the following functions.

Value-at-Risk

$$VaR(\alpha) = \mu + Z(\alpha)\sigma$$

Where (µ) denotes the asset return, and (z) is the value of a 5% confidence level based on a single tail test. Moreover, (α) provides the portfolio value, whereas (σ) reflects the standard deviation of daily asset returns. We also calculated potential risk factors beyond VaR using Conditional VaR (CVaR), a variation of VaR.

$$CVaR(\alpha) = \frac{1}{\alpha}\int_0^{\alpha} VaR(x)dx$$

The conditional component (C) in the following equation appropriately computes the extreme impact. Using the inverse Mills ratio, we analyse conditional expectation.

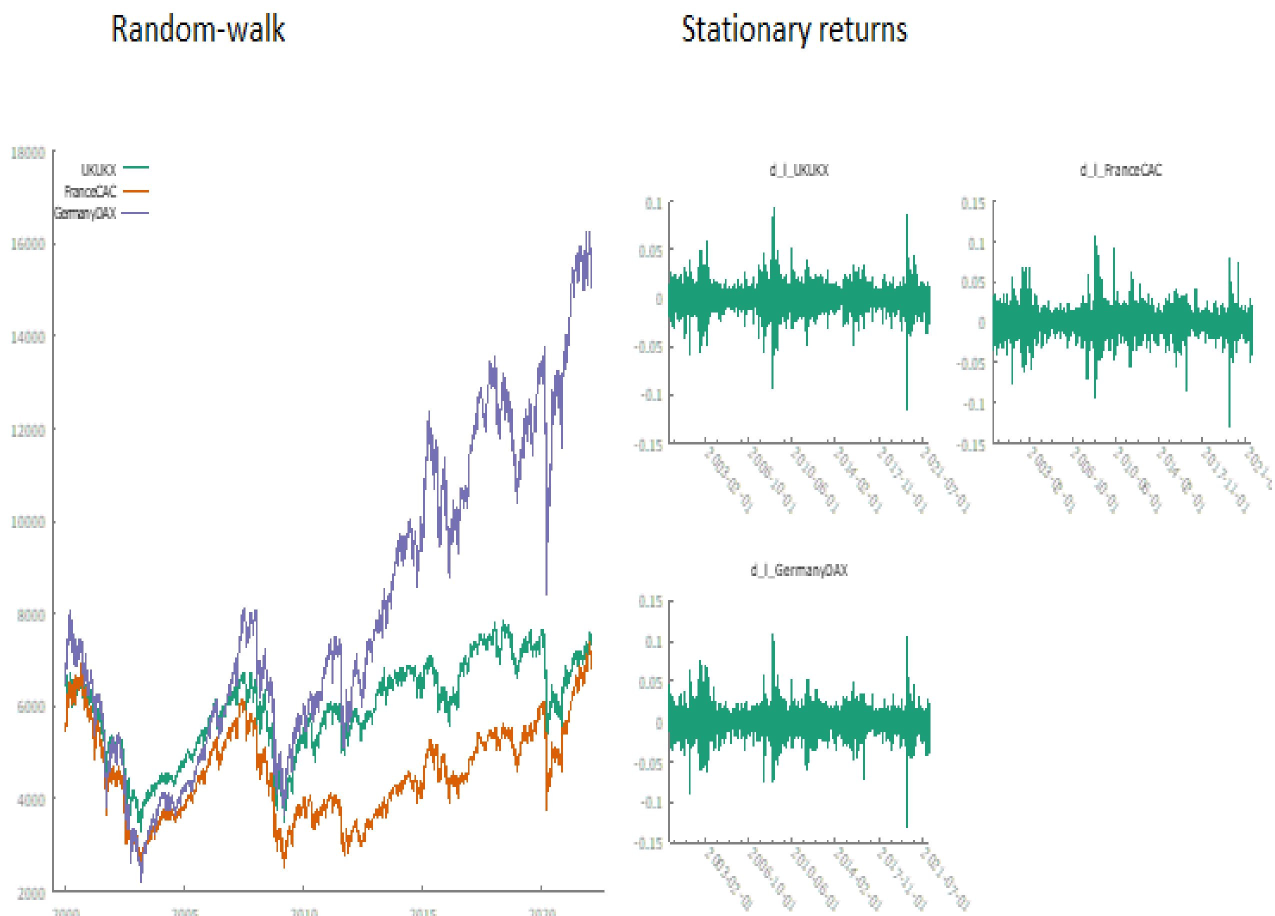
$$CVaR(\alpha) = \mu - \sigma \frac{\varphi\left(\frac{VaR(\alpha) - \mu}{\sigma}\right)}{\Phi\left(\frac{VaR(\alpha) - \mu}{\sigma}\right)}$$

CVaR calculates the acceptable risk based on samples of daily returns (commodity indexes) or the projected shortfall. For discrete distributions, consider the VaR (VaR(σ)X), which is a non-curved and intermittent function of the confidence level (α). As a result, it is difficult to capture non-normal distributions; CVaR modifies this; for (α) = CVaR$\frac{1}{\alpha}\int_0^{\alpha} VaR(x)dx$, confirming that (X) exceeds VaR, resulting in the mean excess loss.

4. Results and Discussion

We start the first portion of the chart; Figure 1 exhibits a random walk for three established financial markets; this indicates that price movements of selected indices are abnormal in behaviour. However, the second part in the same exhibit returns after converting series to log returns and taking the first difference of log returns into account. The data was also subjected to the ADF (Augmented Dickey-Fuller Test), which confirmed that the series was stationary.ADF test testing was reduced to four lags, with AIC as the criterion and sample size 5754 for all three selected samples. We obtained results with a constant and four (1-L) lags by using the model: (1-L) y = b0 + (a-1) * y (-1) +... + e, with (a - 1) as the estimated value: -1.13033, tau c (1) = -35.8771, and asymptotic p-values of 2.211e-34, 6.268e-33, and 7.428e-37 for the United Kingdom, France, and Germany, respectively.

Fig1 Asset returns (Actual series) and First log difference (Stationary) for UK, France and Germany using the daily sample from 01-01-2000 to 31-01-2022



Source: Author's computation using daily closing prices

Table1 Summary Statistics, using the observations 2000-01-03 - 2022-01-31

Variable	Mean	Minimum	Maximum	Std. Dev.	Skewness	Ex. kurtosis
UK - UKX	0	-0.11512	0.093843	0.01165	-0.33852	8.282
France - CAC	0	-0.13098	0.10595	0.0141	-0.21629	6.644
Germany - DAX	0	-0.13055	0.10797	0.01449	-0.1752	6.1244

Source: Author's computation using daily closing prices

During the study period, the UKX, a specimen index of the United Kingdom, created a minimum trading level of 3287 and a maximum trading level of 7877. The CAC, a specimen index of France, traded at 2403 at minimum and 7376 at the highest trading level. The DAX, a German specimen index, traded at 2203 at minimum and 16272 at the highest trading level, indicating a comparatively high growth. The impact of the global financial crisis and present COVID are observed in the actual series and stationary returns of all three European markets. According to the statistics, all markets exhibit negatively skewed returns during the chosen period, with high kurtosis, resulting in a Leptokurtic effect. These values describe the situation where sample distributions are non-normal, and series have a long-left tail. The degree of standard deviation measures the dispersion of the returns (UKX, DAX and CAC). Changes in standard deviation create more fluctuations in prices. In other words, the larger the standard deviation degree, the higher the chances of negative and positive returns.

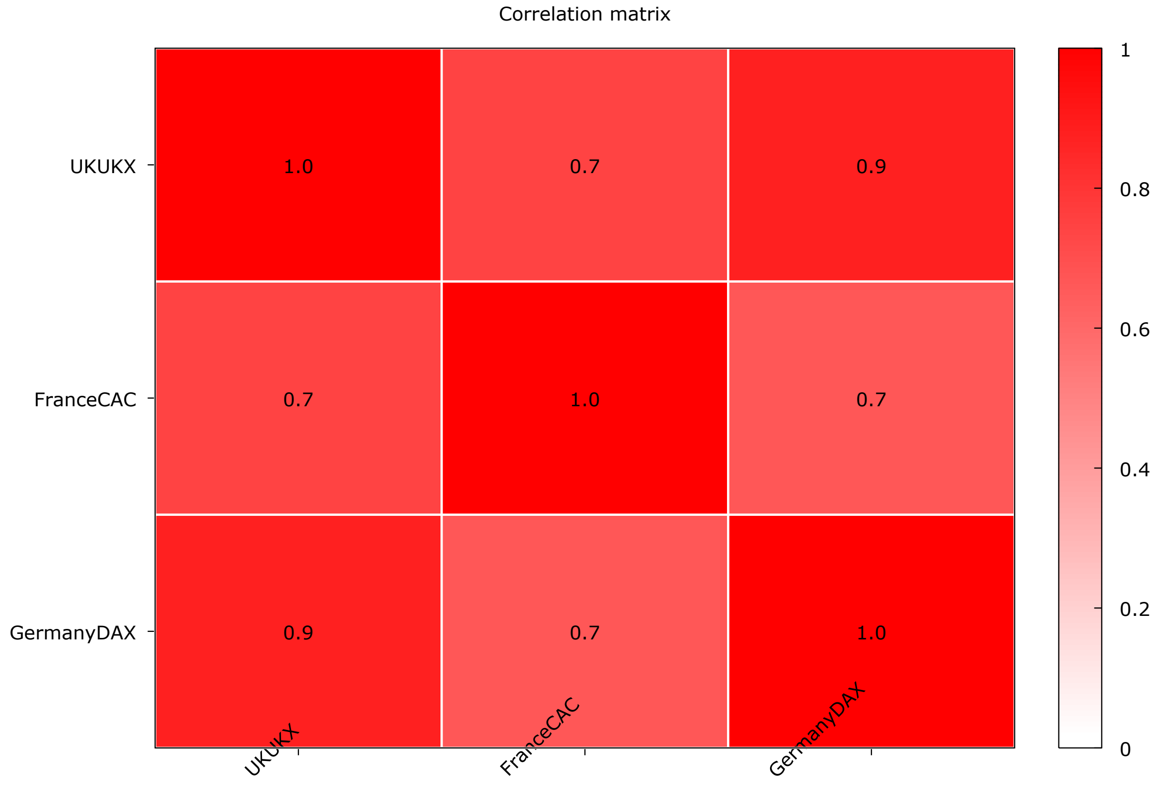
As we can see, the German stock market index (DAX) increased its trading level nearly 16 times to its lowest level, resulting in a significant degree of standard deviation (0.01449) compared to (0.0141) and (0.0116) for France and the United Kingdom, respectively.

Table 2 Correlation Matrix for UK, France, and German stock indices (2000-01-03 - 2022-01-31)

UK UKX (FTSE 100)	France CAC	Germany DAX	
1.0000	0.7411	0.8756	UK UKX (FTSE 100)
	1.0000	0.6629	France CAC
		1.0000	Germany DAX

Source: Author's computation using daily closing prices

Fig2 Correlation Matrix (Box) Chart for UK, France and Germany using daily observations from (2000-01-03 - 2022-01-31)



Source: Author's computation using daily closing prices

Surprisingly, the German stock market (DAX index) is substantially correlated with the UKX or FTSE 100 index (UK) stock market (90 percent), but the CAC index – France is equally correlated with Germany and the UK (70 percent).

Volatility has been an important subject to study and understand. It helps to capture the innovations in the market. Understanding and predicting volatility is vital in finance as results are dynamic and different. We objected to testing the fitness of Bollerslev's (1986) Generalized Autoregressive Conditional Heteroskedasticity to selected sample indices, testing volatility changes before, during, and after the COVID-19 pandemic. The result of GARCH (1, 1) model appears in Table3.

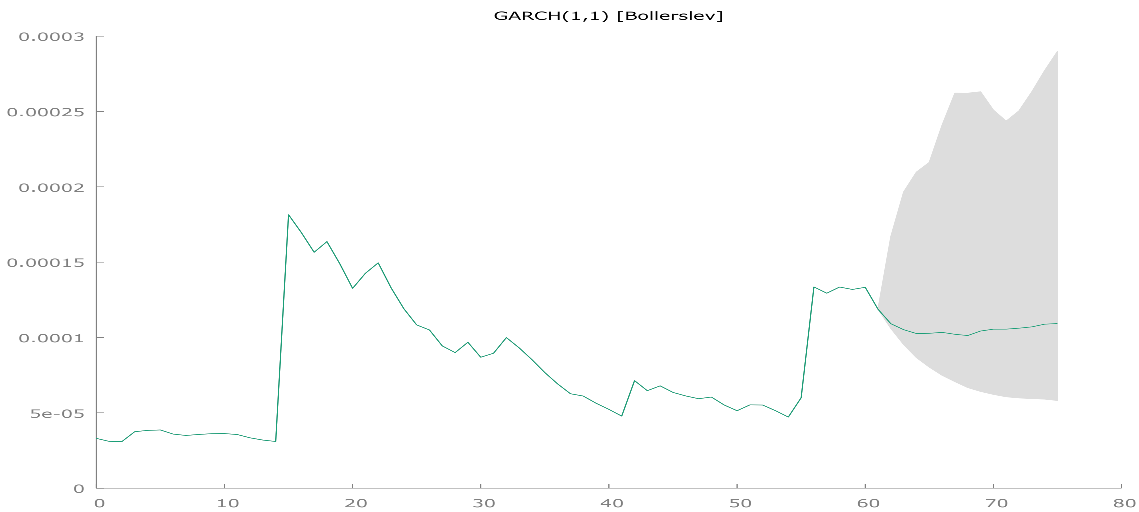
Table 3 GARCH (1, 1) Bollerslev for UK, Germany, and France selected stock indices

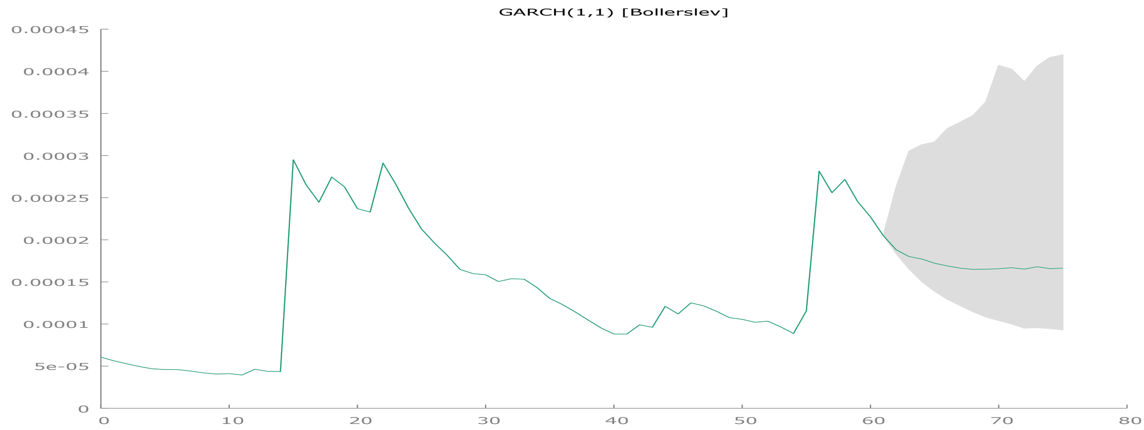
Country	*Const*	*Omega*	*Alpha*	*Beta*	*Sign.*
UK - UKX	0.0003	0	0.1087	0.8749	1%
DAX - Germany	0.0006	0	0.0934	0.8924	1%
CAC - France	0.0005	0	0.1048	0.8807	1%

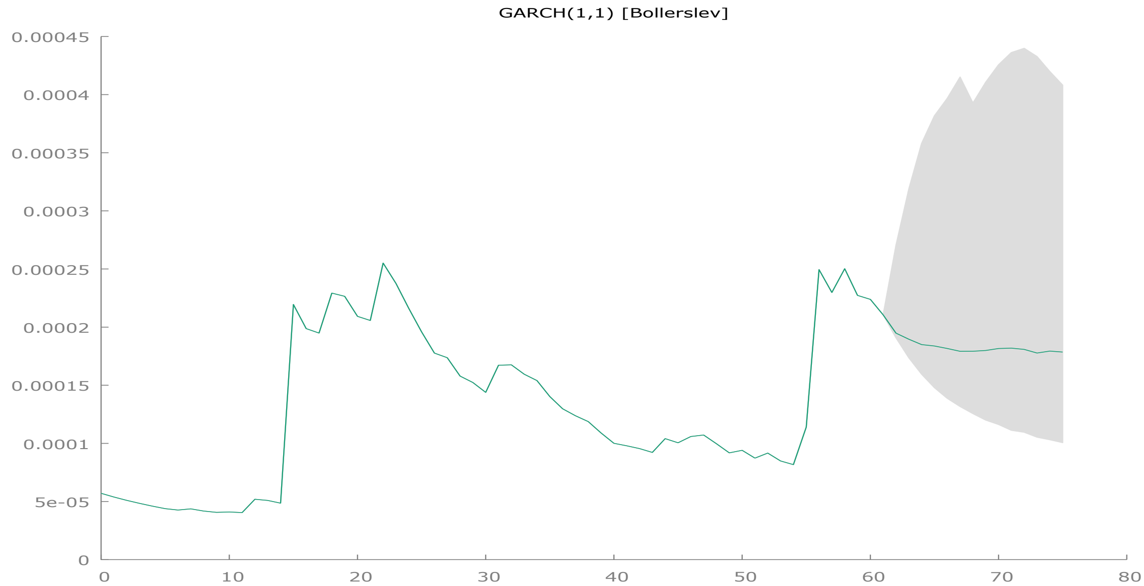
Source: Author's computation using daily closing prices

The GARCH (1, 1) model perfectly fits all sample indices from the United Kingdom, Germany, and France. The constant value is nearly zero for all three samples, indicating no positive returns (from yesterday's purchase and if it sells today). We find a high beta parameter for the DAX compared to the UKX and CAC, indicating a high volatility factor in the German stock market compared to the stock markets in the UK and France. We extended GARCH (1, 1) results to forecast the sample indices, results provided in Fig3 indicating forecasting the movement pattern for selected developed stock indices.

Fig3 GARCH (1, 1) Bollerslev forecast for UK, DAX, and CAC indices







Source: Author's computation using daily closing prices

In the GARCH property, ARCH (α) and GARCH (β) arestatistically significant at 1%, and all coefficients are positive. We note that the sum of α + β is less than one for all three markets;

UKX = α (0.1087) + β(0.8749) = 0.9836

Germany = α (0.0934) + β(0.8924) = 0.9858

France = α (0.1048) + β(0.8807) = 0.9855

We found the sum of (α) and (β) 0.9836, 0.9858 and 0.9855 for UK, Germany and France stock markets, respectively, are less than one, suggesting volatility shocks are quite persistent. ARCH (α) coefficient provides information about the innovations in the stock returns, whereas the (β) coefficient provides information about past news. It indicates that higher degree of (β) coefficient. Furthermore, out of these three samples, we find the magnitude of coefficient (β) comparatively high for DAX (Germany), among other indices. This indicates that the German stock market perceives long memory invariance. We find that estimates of (α) is much smaller than the estimate of (β) in all three sample indices, suggesting adverse shocks do not have a more significant effect on conditional volatility than the positive shocks for the same magnitudes.

The DAX, a German index, was more volatile than the UKX and CAC, indicating a more significant number of shocks that cause high volatility. The fluctuation of standard deviations, as observed, tends to increase the degree of skewness and excess kurtosis. To understand changes in the volatility during the COVID period, we part the entire data into four phases;

Table 4 Volatility statistics for UK, Germany, and France Stock Markets

	Phase – I		*Phase – II*		*Phase – III*		*Phase – IV*	
Variable	*DVP*	*AVP*	*Before COVID*		*During COVID*		*After COVID*	
	ES	ES	*DVP*	*AVP*	*DVP*	*AVP*	*DVP*	*AVP*
UKX	1.16%	18.42%	0.73%	11.54%	1.83%	28.97%	0.79%	12.54%
DAX	1.45%	22.90%	0.87%	13.75%	2.06%	32.63%	0.90%	14.19%
CAC	1.41%	22.29%	0.83%	13.16%	2.04%	32.28%	0.88%	13.92%

*DVP indicates Daily Volatility for the Period
** AVP indicates Annual Volatility for the Period
*** ES, Entire Sample covers (01-01-2000 to 31-01-2022 total 5760 daily OBS)

Volatility in phase – I, as shown in the volatility table, covers the entire sample period, including the global financial crisis and the global pandemic situation of COVID. Most of the world shut down all production in March 2020, and a lockdown was declared. We observed Phase – II, which provides details about yearly trading days (261) and covers almost a year of trading data, indicating that daily volatility in the UK, Germany, and France remained 0.73 percent, 0.87 percent, and 0.83 percent, respectively. When the lockdown was declared the following year, volatility increased exponentially by more than twofold, with daily and annual volatility changes.

Annual volatility for the UK in Phase II exceeds 29%, compared to 11.54 percent the previous year. This is the highest recorded volatility change in a developed market like the United Kingdom. Moreover, the same changes can be seen in Germany (DAX) and France (CAC), where annual volatility exceeded 32% during the COVID impact period. We report that Phase – IV provides critical information, implying that after COVID's impact, daily volatility shifted to a new level. For example, before the COVID phase, daily volatility in the UK was 0.73 percent, but it has now risen to 0.79 percent, and similar increases can be seen in the DAX and CAC stock indices.

The study provides evidence that the DAX, stock market of Germany, despite remained least skewed across the other samples, suggesting that the volatility and response of the asymmetric property also remained high for the German stock market. Volatility parameter property DVP and AVP exhibited in table 4 provides significant and highly relevant information indicating that even during the normal period, the volatility remained high and investors experienced major shocks during the normal trading periods.

On the other side, UK stock market which provided the fat long tail indicating that returns are highly skewed and demonstrating leptokurtic effect (highest across the sample markets) found the be least volatility at the parametric of DVP and AVP across all four phases exhibited in table 4. This explores the volatility market dynamics which was not earlier addressed, particularly when the summary of descriptive statics indicates that least leptokurtic returns with lower degree of skewness, found to be the highest volatility and most responding to market events and news, the German stock market.

Thus, the paper explores and demonstrated the change in volatility dynamics with the change in risk pattern from the sample of UK, Germany and France stock markets, providing significant and robust outcome which adds value to long-term investors as well short-term investors, researchers and readers.

5. Conclusions

The paper presents an empirical analysis based on GARCH (1, 1) model that perfectly models all three European stock markets studied. Moreover, the GARCH (1,1) model results add the Coronavirus (COVID-19) pandemic variable to the conditional mean and conditional variance equation. We discovered that (1) volatility in the UK, Germany, and France is persistent, (2) purchase made yesterday does not result in a positive value if sold today, (3) the degree of standard deviation and coefficient (β) for the DAX, Germany, is higher than for the UK and France, (4) the German stock market is strongly correlated with the UK stock market, and (5) volatility statistics provide changes in trading patterns for before, during, and after the COVID period. The results reveal a significant positive impact of the virus on the conditional variance for all the indices.Further, paper exhibited the changes in dynamics of volatility during the different period with changes in pattern and magnitude of shocks.

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