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REVISITING THE SUDDEN CHANGES AND VOLATILITY PERSISTENCE IN EUROPEAN CAPITAL MARKETS: SOME EMPIRICAL EVIDENCE

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Abstract:
Understanding the behavior of market volatility is crucial for asset pricing, portfolio selection, risk management, and trading strategies. The standard Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model assumes that there is no shift in variance, hence its inability to produce a good estimate of volatility persistence. Thus, this research paper re-examines volatility persistence as well as the sudden changes in variance for some major European capital markets- French CAC 40, German DAX 30, and Britain's FTSE 100 stock. The study captures the simultaneous shifts in variance, detected by the iterated cumulative sums of squares (ICSS) algorithm, incorporated into the multivariate BEKK-GARCH model. Information obtained shows that the detected changes correspond to both global and domestic events. Results also showed that volatility persistence is reduced in a controlled volatility change model compared to a model ignoring volatility changes. The implication of these results indicates that previous studies on European volatility persistence may have reported overestimated results.

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INTRODUCTION

Volatility refers to the amount of risk or uncertainty related to an asset. But measuring and predicting these uncertainties has been a key challenge for financial investors, academia, and risk managers. Understanding volatility measurement is crucial in monetary policies, investment decisions, pricing, risk management, and banking security valuation (Fakhfekh, Hachicha, Jawadi, Selmi, & Cheffou, 2016). However, financial market linkages otherwise known as volatility transfer among capital markets have been used to examine financial integration as well as cross-border transmission of the capital market. Whilst many studies documents evidence of a high level of financial integration between developed countries (Ma, Wahab, & Zhang, 2019; Mensi, Boubaker, Al-Yahyaee, & Kang, 2018; Gupta, Kollias, Papadamou, & Wohar, 2018; Shah, Schmidt-Fischer, Malki, & Hatfield, 2019; Guesmi, Teulon, & Ftiti, 2014; etc), others have reported evidence on the relationship between a developing market and frontier markets (Balcilar, Demirer, & Hammoudeh, 2019; McMillan, Ziadat, & Herbst, 2021), etc.

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However, financial markets volatility has been extensively studied using the univariate GARCH model, particularly high-frequency data to examine the volatility persistence. Unfortunately, the GARCH model does not incorporate sudden changes in volatility (Wang & Moore, 2009), hence its inability to capture sudden shifts in volatility. But ignoring the deterministic regime shifts in GARCH model estimation, volatility persistence might be overestimated. However, recent econometrics approaches such as Kumar & Maheswaran (2012); have shown that the iterated cumulated sums of squares (ICSS) algorithm techniques have a better capacity to detect locations as well as periods of sudden changes in volatility. The ICSS developed by Inclan & Tiao (1994) is an improvement to several previous methods for the detection of sudden changes in volatility. However, many of these studies employed the univariate models with a handful of researchers such as Ewing & Malik (2005) using the bivariate BEKK-GARCH model and ICSS to investigate sudden change phenomena. Although numerous research papers such as Ahmed & Huo (2021); Koulakiotis, Babalos, and Papasyriopoulos (2016); Jayasinghe, Tsui, & Zhang (2014); etc., have examined financial markets volatility spillover effects, but to the best of our knowledge, no paper has mounted the sudden changes in volatility on a trivariate GARCH model to examine volatility persistence.

This research paper simultaneously examines the impacts of sudden changes in the persistence of volatility for three major European capital markets which are seen by many market participants as a key proxy for the broader European market (Kuepper, 2020), These markets include the French CAC 40 stock index, the German DAX 30 index, and the British FTSE 100 index. The ICSS algorithm and trivariate BEKK-GARCH model are employed to capture sudden shifts and volatility persistence. Europe constitutes a remarkable part of the world's global market capitalization, hence, the reason why its markets are a major target for international business investors. The report of 2019 global economy rankings based on GDP shows that Germany has the fourth largest economy, closely followed by the UK, which is sixth globally, and the French economy ranked the seventh largest. This and a few other reasons why the European markets are extremely important for international capital market participants. Therefore, a good knowledge of how such social, economic, or political events relate to the changes observed in volatility will be of tremendous benefit to Europe policymakers, academia, and international business investors.

Specifically, this research contributes to the literature in three folds. Firstly, this paper examines the role sudden change in variance plays in the transmission process of three major European stock markets by using the ICSS algorithm to detect the periods of changes in volatility. Secondly, whether ignoring such changes can induce volatility persistence of financial markets returns. Thirdly, unlike previous studies which employ either the univariate or bivariate model, this paper incorporates the sudden change information into the multivariate VAR-BEKK-GARCH model to capture the volatility persistence of three European capital market returns. This partly extends Ewing & Malik's (2005) literature. Our empirical findings reveal that models with controlled volatility shifts have considerably decreased in volatility transmission, hence the spillover effects are reduced. This indicates that sudden changes not accounted for can lead to the overestimation of volatility transmission among the conditional variances of capital market returns.

The remainder of the paper is organized as follows. Section 2 briefly presents the literature review of related studies on the sudden change in volatility. Section 3 shows the methodology of the ICSS algorithm, the multivariate GARCH models as well as the sample data. Section 4 discusses the estimation results of the ICSS algorithm. Section 5 is the final section of the research paper which provides some concluding remarks.

REVIEW OF RELATED LITERATURE ON SHIFTS IN VARIANCE

To model the volatility persistence of the capital market, different GARCH-type models have been employed. And this includes GARCH, IGARCH, FIGARCH, HYGARCH, etc. Tissaoui & Azibi's (2019) research paper investigates the volatility risks between the Saudi stock return and other international stocks such as US., China, France, UK., Germany, etc. They employed the DCC-GARCH (1.1) and cross-correlation function (CCF) approach to examine the short-run and long-run persistence of shocks. The DCC-GARCH detects the short-run and long-run persistence of shocks on the dynamic conditional correlation in most capital markets. Aliyev, Ajayi, & Gasim (2020), employs EGARCH and GJR-GARCH model to estimate the nonfinancial volatility, and innovative and hi-tech stock indexes. Their results show that negative shocks are higher than positive shocks of the same magnitude. Zeng, Jia, Su, Jiang, & Zeng (2021), used the BEKK-GARCH model to analyze the spillover effect between the EUA and CER markets. Their results revealed the existence of asymmetric volatility transmission between EUA and CER markets. The volatility spillover effects of U.S. and BRICS capital markets were examined by McIver & Kang (2020) using the spillover index and the DECO-GJR-GARCH model. Their model confirmed that financial crises increase contagion effects, with the U.S. capital market being the major transmitter of return and volatility. Stock index volatility is a feature of both long memory and structure break, hence the use of the AFIGARCH model is appropriate (Luo & Huang 2019). Mensi, Hammoudeh, Nguyen, & Kang, (2016) employed the bivariate DCC-FIAPARCH model, modified ICSS algorithm, and VaR to capture the volatility spillovers, detect sudden changes and portfolio market risks respectively between the U.S. market and BRICS (Brazil, Russia, India, China, and South Africa) countries stock markets.

However, financial asset volatility can be influenced significantly by occasional changes as a result of domestic and/or global economic, social, and political events. The results of such sudden changes can lead to persistence in time-varying conditional volatility. Some of the early and popular literature examined the sudden changes phenomena to get a good estimate of volatility persistence. They employed the ARCH and GARCH models respectively in their empirical analysis. Their results show a significant reduction in volatility persistence when the sudden change was accounted for in their model. Raju & Shirodkar, (2020) investigate the impact of stock future on India's stock volatility by incorporating the sudden breaks using the ICSS algorithm and AR (1)-GARCH (1, 1) model for thirty (30) most liquid and actively traded stocks and futures. Their study reveals evidence of a decline in unconditional volatility for almost all the stocks examined. Sudden changes in volatility persistence have played a major impact on the estimated hedge ratio, but the use of dummy variables for induced sudden change showed to have eliminated the associated bias (Caporin & Malik, 2020)

Inclan & Tiao's (1994) research paper shows the inability of the GARCH models to capture sudden changes that occurs in financial markets. For this reason, they proposed the ICSS algorithm which can detect sudden changes in the volatility of asset returns. Lee & Chou, (2020) used the EGARCH-DCC model to evaluate the correlation between Asia and the United States (U.S.) and applied the ICSS to obtain the sudden break. Their result reveals that when detected sudden changes in volatility are fussed in the GARCH model, volatility persistence declines. Using a Monte Carlo simulations study, empirical research revealed that size bias is crucial for GARCH processes. Thus, they developed the modified ICSS test to detect the period and shifts in volatility. Their empirical research failed to detect structural breaks in volatility when the outliers are considered but detected structural breaks when the original series was applied. Adesina (2017) employed the univariate GARCH model with structural shifts to explore the volatility persistence of the Brexit-vote break. Their results show that volatility persistence without structural break GARCH model performs equally as the augmented GARCH with structural break model. Vivian & Wohar's (2012) paper also used the ICSS procedure and GARCH model to examine the effects of structural breaks in the commodity spot market index. Other studies that have employed the ICSS algorithm to detect sudden changes in volatility include, Kumar & Maheswaran (2012); Wang & Moore (2009), etc.

Borzykh & Khasykov, (2018) constructed a hybrid algorithm for the detection of structural breaks. The detected break showed to capture significantly related events (Gazprom). Morales & Andreosso-O'Callaghan (2014) employed the ICSS algorithm to examine the volatility persistence of oil returns and three global equity indices (Dow Jones Industrial, FTSE 100, and Nikkei 225). They observed high volatility persistence between these markets during economic and financial shocks. Ngene, Tah, & Darrat, (2017) research paper shows that volatility persistence may be an artifact of short memory confronted with some African stock markets. IT-ICSS algorithm showed to exhibit significant power and size properties when combine with Yang and Zhang's (YZ) estimator compare to when it is applied with the demeaned squared returns. (Kumar, 2016). Kumar & Maheswaran (2013), examines the power and size of Inclan and Tiao's (1994) ICSS algorithm for detecting sudden changes in volatility. Their finding showed that the detected breaks correspond to macroeconomic events. Todea & Platon, (2012) examines the structural breaks and volatility persistence in four Central and Eastern European (CCE) financial markets using the ICSS algorithm. Their results show a significant reduction in volatility when structural breaks are taken into consideration.

This paper examines the role shifts in variance play in the transmission process of three major European stock markets using the ICSS algorithm. To put it succinctly, we examine empirically whether the fusion of sudden changes to VAR-BEKK-GARCH models reduces the asymmetry and volatility persistence in three European capital markets. Using the multivariate GARCH model, the sudden change in variance can be linked across variables with strong transmission among second moments.

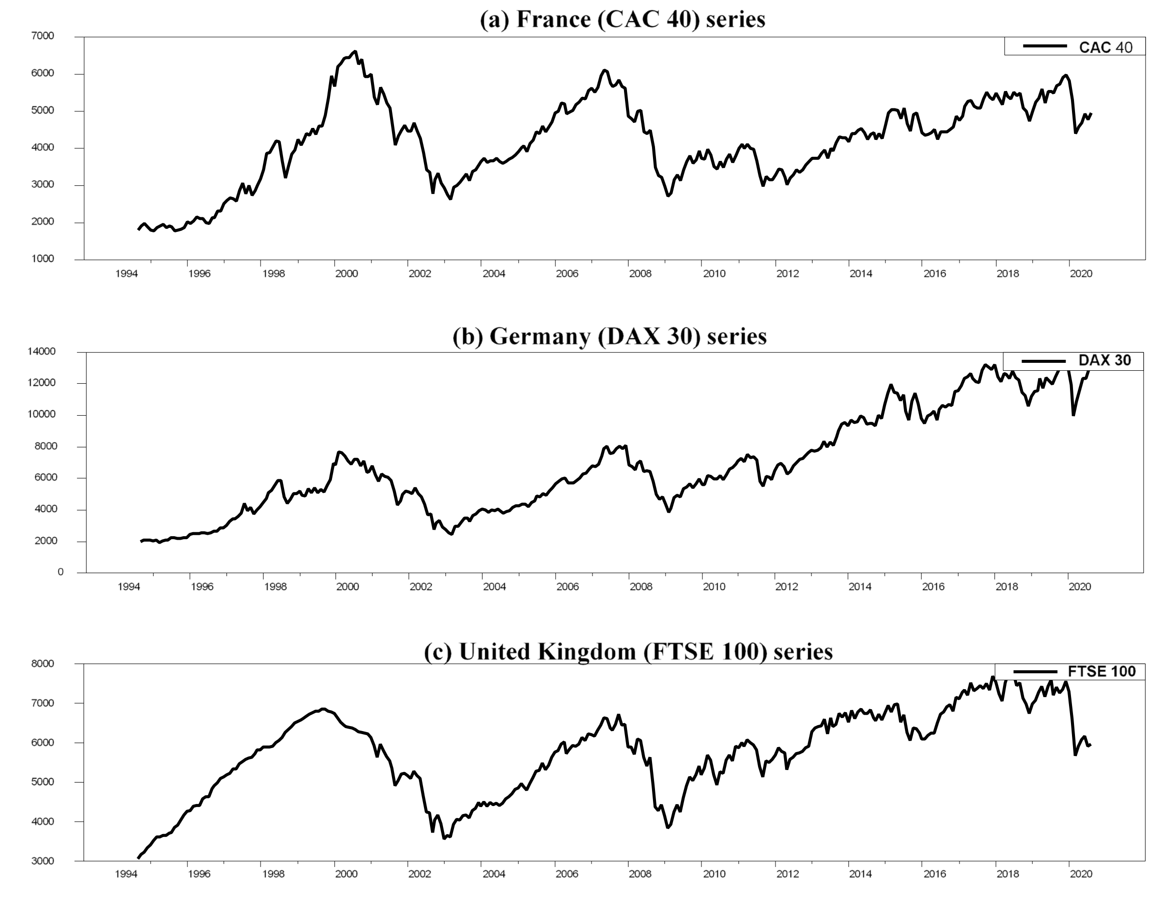
METHODOLOGY & DATA

The monthly closing price indexes of three popular European capital markets are used as the dataset in the research paper. These capital market indexes include the French CAC 40 stock index, the German DAX 30 index, and the British FTSE 100 index. These data range from the 1st of September 1994 to the 1st of August 2020 yielding a total observation of 312 for each series. The behavior of these series has been shown in Figure 1. However, Table 1 describes the properties of the three markets' returns. With a standard deviation of 21.6%, the German market appears the most volatile among the three European indexes examined in this research paper. This is followed by the French market with a standard deviation of 13.3%, while the United Kingdom market index has the least standard deviation. Germany and the United Kingdom indexes have negative excess kurtosis indicating platykurtic while the French index has leptokurtic.

Table 1. Descriptive Statistics for Indexes

Variables	Obs.	Mean	S. D	Min.	Max.	Skewness	Kurtosis (ex)
France CAC 40	312	3.600	0.133	3.249	3.821	-0.884	0.339
Germany DAX 30	312	3.782	0.216	3.282	4.122	-0.349	-0.572
UK. FTSE 100	312	3.751	0.087	3.484	3.889	-0.754	-0.076

Figure 1. Monthly stock prices series: (a) CAC 40; (b) DAX 30; (c) FTSE 100.



Detecting points of the shift in variance

Suppose ε_t has a zero mean with unconditional variance σ^2. And the variance within the interval be given as σ_j^2, j=0,1,…,N_T. Where N_T indicates the total number of variance changes in T observation, then the values, $1<k_1<k_2<\ldots k_{N_T}<T$ are the points where the changes occurred (Inclan and Tiao, 1994).

$$\sigma_t^2=\tau_0^2 \quad \text{for} \quad 1< t < k_1 \tag{1a}$$

$$\sigma_t^2=\tau_1^2 \quad \text{for} \quad k_1< t < k_2 \tag{1b}$$

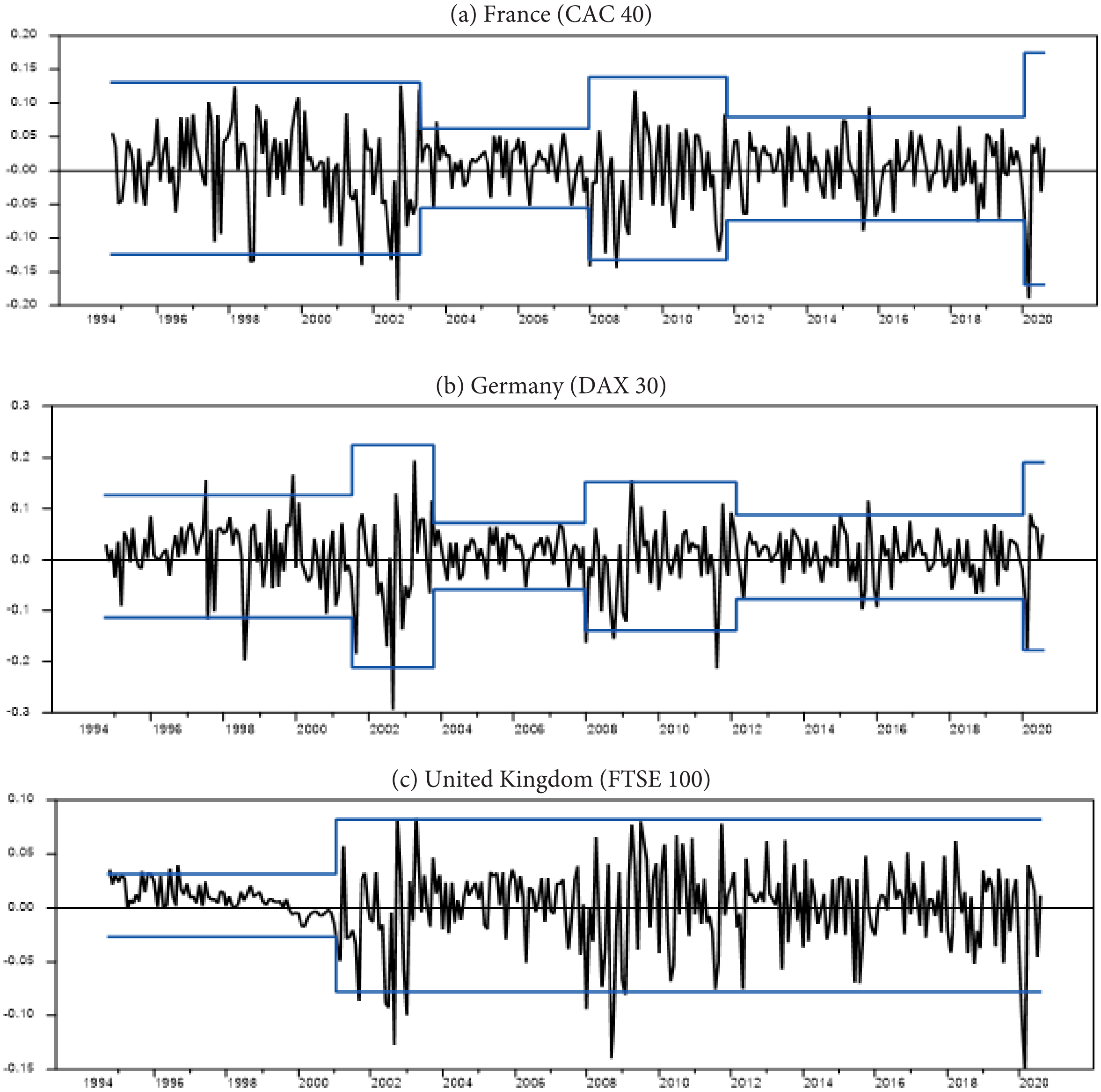
$$\sigma_t^2=\tau^2_{NT} \quad \text{for} \quad k_{NT}< t < T \tag{1c}$$

The number of changes in variance as well as the time point are detected by the cumulative sum of squares (CSS). Let $C_k=\Sigma^k_{t=1}\varepsilon_t^2$, k=1,…,T, be the CSS from the first observation to the point in Kth time. And the D_k statistic is given as

$$D_k= C_k/C_T= k/T \qquad k=1,\ldots,T \qquad \text{with } D_0=D_T \tag{2}$$

where C_T is the whole sample period sum of squared residuals, the D_k statistic will fluctuate around zero if a sudden shift does not occur in the variance of the series. And when plotted against k, it resembles a horizontal line. But if there are shifts in variance, the value of the D_k statistic will either drift above or below zero. And significant sudden changes in variance are detected. This is based on the critical values obtained from the D_k statistic under the null hypothesis of homoscedasticity. In other words, if the max. absolute value of D_k is greater than the critical value, the H_0 of homoscedasticity is rejected. Let the value of $Max_k |D_k|$ reached be k^*, and if $Max_k \sqrt{(T/2)}|D_k|$ value falls outside the predetermined range, then the value of k^* indicates the period in the series when variance changes. A critical value of 1.36 indicates the 95th percentile of the asymptotic distribution of $Max_k \sqrt{(T/2)}|D_k|$ is applied (Kumar & Maheswaran, 2012). The upper and lower boundaries of D_k plots are set at ± 1.36. And if the statistical values fall outside these boundaries, a sudden change in variance is detected.

Figure 2. Monthly stock returns: (a) CAC 40; (b) DAX 30; (c) FTSE 100.



***Note:** The Blue line indicates the bounds which are set at ±3 standard deviation, and the sudden change is detected using the ICSS algorithm.*

The Multivariate GARCH model

The three capital markets returns are calculated using the price indexes,

$$R_t=100*\ln(P_t/P_t-1) \tag{3}$$

The following mean equations are estimated for each capital market's return and the returns of other lagged to analyze return spillover effects.

$$R_{it}=u_i+\varphi_i R_{it}-1+\varepsilon_{it} \tag{4}$$

where R_{it} is the capital index return i at time t and u_i is the drift coefficient, and ε_{it} indicates the error term for index i at time t. The optimal lag length of VAR based on Akaike (AIC) which minimizes the information criteria indicates lag 1. The Vector Autoregressive (VAR) models and the trivariate VAR (1) are given as,

$$\begin{pmatrix} r_{1,t}^{CAC} \\ r_{2,t}^{DAX} \\ r_{3,t}^{FTSE} \end{pmatrix} = \begin{pmatrix} u_{1,t}^{CAC} \\ u_{2,t}^{DAX} \\ u_{3,t}^{FTSE} \end{pmatrix} + \begin{pmatrix} \varphi_{1,1} & \varphi_{1,2} & \varphi_{1,3} \\ \varphi_{2,1} & \varphi_{2,2} & \varphi_{2,3} \\ \varphi_{3,1} & \varphi_{3,2} & \varphi_{3,3} \end{pmatrix} \begin{pmatrix} r_{1,t-1}^{CAC} \\ r_{2,t-1}^{DAX} \\ r_{3,t-1}^{FTSE} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t}^{CAC} \\ \varepsilon_{2,t}^{DAX} \\ \varepsilon_{3,t}^{FTSE} \end{pmatrix} \tag{5}$$

Where r_t is a 3X1 yearly market returns vector at time t. In the trivariate VAR (p) model, $r_{1,t}$ indicate the yearly CAC 40 market return, $r_{2,t}$ shows DAX 30 market return, and $r_{3,t}$ represent FTSE 100 market returns. The diagonal elements of matrix φ_i are the various market returns one period lagged, while the off-diagonal elements $\varphi_{i,j}$ indicate the mean spillover effect across markets. The 3x1 vector u_i contains constants.

To ensure that the covariance matrix is positive and semi-definite, we choose the BEKK- a model of Engle & Kroner (1995). And the BEKK parameterization can be written as,

$$H_t= C'C+B'H_{t-1}B+A'\,\varepsilon_{t-1}\,\varepsilon'_{t-1}A \tag{6}$$

Where C,A,B, and H are parameters of 3x3 matrices, C is the lower triangular, H_t indicates the model conditional variance, ε_t represents vectors of unexpected shocks from the VAR(1) model, A is a parameter measures the extent the conditional variances correlate with past squared errors, B is the extent the conditional variances are related to past conditional variances. From equation (6), we set up the multivariate GARCH conditional variance equations in line with Ahmed & Huo's (2021) research papers. Thus,

$$\begin{aligned} h_{CAC\,40,t} &= C_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + a_{21}^2\varepsilon_{2,t-1}^2 + a_{31}^2\varepsilon_{3,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ &+ 2a_{11}a_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{21}a_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{11}^2h_{11,t-1} + b_{21}^2h_{22,t-1} \\ &+ b_{31}^2h_{33,t-1} + 2b_{11}b_{21}h_{12,t-1} + +2b_{11}b_{31}h_{13,t-1} + 2b_{21}b_{31}h_{23,t-1} \end{aligned} \tag{7a}$$

$$\begin{aligned} h_{DAX\,30,t} &= C_{12}^2 + C_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + a_{32}^2\varepsilon_{3,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ &+ 2a_{12}a_{32}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{22}a_{32}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{12}^2h_{11,t-1} + b_{22}^2h_{22,t-1} \\ &+ b_{32}^2h_{33,t-1} + 2b_{12}b_{22}h_{12,t-1} + +2b_{12}b_{32}h_{13,t-1} + 2b_{22}b_{32}h_{23,t-1} \end{aligned} \tag{7b}$$

$$\begin{aligned} h_{FTSE100,t} &= C_{13}^2 + C_{23}^2 + C_{33}^2 + a_{13}^2\varepsilon_{1,t-1}^2 + a_{23}^2\varepsilon_{2,t-1}^2 + a_{33}^2\varepsilon_{3,t-1}^2 + 2a_{13}a_{23}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ &+ 2a_{13}a_{33}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{33}a_{33}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{13}^2h_{11,t-1} + b_{23}^2h_{22,t-1} \\ &+ b_{33}^2h_{33,t-1} + 2b_{13}b_{23}h_{12,t-1} + 2b_{13}b_{33}h_{13,t-1} + 2b_{23}b_{33}h_{23,t-1} \end{aligned} \tag{7c}$$

Multivariate GARCH model with sudden changes

Borzykh & Yazykov (2019) proposed the KS method based on Kolmogorov-Smirnov statistics to detect structural breaks for the GARCH model. The result showed to be highly competitive with a high probability of type I error. Other numerous studies have shown that empirical analysis of sudden changes in variance incorporated into GARCH models led to an increase in persistence in volatility. Ewing & Malik (2005) argues that to obtain conditional variance with reliable estimates, there is a need to incorporate the sudden change in variance into the GARCH model. They examined the persistence of volatility of two series, first by identifying the sudden shifts in variance with the aid of the ICSS algorithm incorporating the regime shift in a bivariate GARCH model. However, this paper investigates the volatility persistence of three major and popular European stock markets - the French CAC 40 stock index, the German DAX 30 Index and the British FTSE 100 index in a trivariate GARCH model framework. In line with Ewing & Malik's (2005) study, equation (6) indicates a model with no sudden change dummy (ignoring sudden change), and equation (8) shows the incorporation of a sudden change dummy (controlling sudden change) in a trivariate GARCH model.

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + \sum_{i=1}^{n} D_i'X_i'XD_i \tag{8}$$

Where D_i is a 3X3 parameters square matrix, and X_t is the incorporated 1X3 vector of control variables, n is the number of breakpoints observed in variance. Equation (9) shows the maximum likelihood function with normally distributed errors.

$$H(\theta) = -Tln(2\pi) - \frac{1}{2}\sum_{i=1}^{T}\left(ln\left|H_t\right| + \varepsilon_t' H^{-1}\varepsilon_t\right) \tag{9}$$

EMPIRICAL RESULTS

To determine the number of sudden changes, this research paper employs the ICSS algorithm proposed by Inclán & Tiao (1994) to calculate the standard deviations between change points. The detected sudden change is incorporated into the VAR-BEKK-GARCH model for estimation. To avoid mistakes in the matrix's calculation, the online matrix calculator shown at https://matrixcalc.org/en/ is employed for computations. The multivariate GARCH model in BEKK form is estimated in the BFGS optimization algorithm by the econometrics software package RATS 10.0 (Regression Analysis of Time Series) developed by Estima. Figure 2 (a) – 2 (c) illustrates the points of sudden change between bands ±3 standard deviations of capital market return for each series. Table 2 shows the numbers of sudden changes detected, period, volatility as well as the events which correspond to the sudden change periods. Whilst four change points were detected for French CAC 40 returns in five different periods, five regime shifts in six periods were identified for the German DAX 40 returns. The United Kingdom indicates one sudden change for the period examined. In September 1994, there was a simultaneous sudden change increase in the volatility of the French CAC 40, DAX 30, and UK FTSE 100 series. But only the French CAC 40 series is shown to be significant. There was another significant simultaneous increase in the volatility of the French CAC 40 and DAX 30 series which started in June 2008. This could have been occasioned by the 2008/2009 global financial crises. Some global events have been shown to have occurred around or corresponded to the period these change points in volatility happened. The early 2000 recession as well as the 2008/2009 global financial crises have been shown to correspond to the time points of sudden changes in the volatility of market returns. The impact of these events affected the financial markets, hence a decline in capital markets.

Table 2. Sudden shifts in variance in the markets

Series (Country)	Nos. of Change Points Detected	Period (Dates)	S. D	Corresponding Events
France CAC-40	04	1994:09 – 2003:04*	0.179	Early 2000s recession
		2003:07 – 2008:03	0.083	
		2008:06 – 2012:05*	0.051	The global financial crisis
		2012:07 – 2020:02	0.062	
		2020:04 – 2020:08	0.015	
Germany DAX 30	05	1994:09 – 2001:06	0.193	
		2001:11 – 2004:07*	0.094	Early 2000s recession
		2004:12 – 2008:04	0.089	
		2008:06 – 2013:05*	0.074	The global financial crisis
		2013:07 – 2020:01	0.054	
		2020:03 – 2020:08	0.042	
The UK. FTSE-100	01	1994: 09 – 2001:01*	0.102	Early 2000s recession

Note: ** indicates the period of increase in volatility, Periods are detected by the ICSS algorithm.*

Table 3. Multivariate VAR-BEKK-GARCH (1,1) model Ignoring volatility changes

France conditional variance equation:

$$h_{11,t} = 4.569X10^{5} + 0.132\varepsilon^{2}_{1,t-1} - 0.0067\varepsilon^{2}_{2,t-1} + 0.0023\varepsilon^{2}_{3,t-1} - 0.059\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.034\varepsilon_{1,t-1}\varepsilon_{3,t-1} - 0.0078\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.748h_{11,t-1} + 0.00057h_{22,t-1} + 0.0016h_{33,t-1} + 0.041h_{12,t-1} + 0.0709h_{13,t-1} + 0.0019h_{23,t-1}$$

Germany conditional variance equation:

$$h_{22,t} = 1.823X10^{4} + 2.265X10^{5} + 0.0196\varepsilon^{2}_{1,t-1} + 0.0309\varepsilon^{2}_{2,t-1} + 0.011\varepsilon^{2}_{3,t-1} + 0.0499\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.0298\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.0369\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.0154h_{11,t-1} + 0.976h_{22,t-1} + 0.0051h_{33,t-1} - 0.245h_{12,t-1} - 0.0096h_{13,t-1} + 0.0771h_{23,t-1}$$

UK. conditional variance equation:

$$h_{33,t} = 1.36X10^{4} + 1.0X10^{-12} + 0.005\varepsilon^{2}_{1,t-1} + 0.003\varepsilon^{2}_{2,t-1} + 0.403\varepsilon^{2}_{3,t-1} - 0.008\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.090\varepsilon_{1,t-1}\varepsilon_{3,t-1} - 0.080\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.004h_{11,t-1} + 0.001h_{22,t-1} + 0.675h_{33,t-1} - 0.005h_{11,t-1} - 0.113h_{13,t-1} + 0.065h_{23,t-1}$$

Volatility persistence:	
France (CAC 40)	0.965
Germany (DAX 30)	0.907
The UK. (FTSE 100)	0.743

Notes: *$h_{11,t}$ indicates the conditional variance for France's CAC-40 market return series, $h_{22,t}$ indicates the conditional variance for Germany's DAX-30 return series, and $h_{33,t}$ represent the conditional variance for the UK. FTSE-100 market return.*

To determine the sudden changes that are statistically significant and much such variance shifts affect the three financial markets' volatility persistence, we estimate the BEKK-GARCH model. Tables 3 and 4 shows the variance equation estimates of the trivariate GARCH model with BEKK parameterization shown in equation 7a – 7c. To evaluate the persistence of volatility in the VAR-BEKK-GARCH framework, the sum of the squared error terms, cross-product of error terms, co-variances, and the coefficients of lagged variances are computed. The trivariate GARCH model ignoring sudden changes shows market volatility persistence to be close to unity. This indicates that the shift in variances in the series of such markets may have a permanent impact on volatility. However, the volatility of French's CAC 40 and the United Kingdom's FTSE-100 indexes showed to have the most and least volatility persistence, respectively. But when sudden change effects were controlled in the model, results shown in Table 4 reveal that the volatility persistence decreases compare to results indicated in Table 3. Comparing volatility persistence between a model that controls and a model that does not control sudden changes, Table 5 indicates that there is a large decline in persistence for CAC 40 and FTSE-100 stock returns series with a decline rate of 0.234 and 0.219 respectively, and DAX 30 index declined with 0.106 rates. In other words, ignoring sudden changes in a model can increase the volatility persistence of the conditional variance in the French CAC 40, DAX 30, and UK FTSE 100 index series. Therefore, our results are in line with the results and views of Wang and Moore (2009) that if the sudden changes in the conditional variance are ignored, the GARCH model overestimates volatility persistence.

Table 4. Multivariate VAR-BEKK-GARCH (1,1) model with controlled volatility changes

France conditional variance equation:

$$h_{11,t} = 3.572X10^{8} + 0.272\varepsilon^{2}_{1,t-1} + 0.110\varepsilon^{2}_{2,t-1} + 0.026\varepsilon^{2}_{3,t-1} - 0.346\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.171\varepsilon_{1,t-1}\varepsilon_{3,t-1} - 0.109\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.543h_{11,t-1} + 0.0038h_{22,t-1} + 0.0076h_{33,t-1} - 0.091h_{12,t-1} + 0.125h_{13,t-1} - 0.011h_{23,t-1}$$

Germany conditional variance equation:

$$h_{22,t} = 6.756X10^{7} + 2.656X10^{8} + 1.147\varepsilon^{2}_{1,t-1} + 0.334\varepsilon^{2}_{2,t-1} + 0.018\varepsilon^{2}_{3,t-1} - 1.230\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.241\varepsilon_{1,t-1}\varepsilon_{3,t-1} - 0.153\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.0003h_{11,t-1} + 0.411h_{22,t-1} + 0.044h_{33,t-1} - 0.024h_{12,t-1} - 0.007h_{13,t-1} + 0.261h_{23,t-1}$$

UK. conditional variance equation:

$$h_{33,t} = 1.36X10^{-4} + 1.0X10^{-12} + 0.005\varepsilon^{2}_{1,t-1} + 0.003\varepsilon^{2}_{2,t-1} + 0.403\varepsilon^{2}_{3,t-1} - 0.008\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.090\varepsilon_{1,t-1}\varepsilon_{3,t-1} - 0.080\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.004h_{11,t-1} + 0.001h_{22,t-1} + 0.675h_{33,t-1} - 0.005h_{11,t-1} - 0.113h_{13,t-1} + 0.065h_{23,t-1}$$

Volatility persistence:	
France (CAC 40)	0.731
Germany (DAX 30)	0.891
The UK. (FTSE 100)	0.464

Notes: *$h_{11,t}$ indicates the conditional variance for France's CAC-40 market return series, $h_{22,t}$ indicates the conditional variance for Germany's DAX-30 return series and $h_{33,t}$ represent the conditional variance for the UK. FTSE-100 market return.*

In addition to results shown in Tables 3 and 4, the variance's equations estimated coefficients shown in equations 7a – 7c and reported in Table 6, decrease when sudden change is controlled. That is, there is a strong GARCH effect in the conditional variance's parameters for the markets. For example, when the sudden change was ignored, the French's CAC 40 variance coefficient shown as B(1,1) is 0.962, but when the constraints were controlled, the variance coefficient dropped to 0.668. Similarly, the German DAX 30 variance coefficient expressed as B(2, 2) declined from 0.902 to 0.489. At the same time, the United Kingdom's FTSE 100 variance coefficient B(3, 3) also decrease from 0.884 to 0.240. The multivariate GARCH test (MVARCH TEST) indicates that the residuals from the VAR-BEKK-GARCH model are serially uncorrelated showing no ARCH effects - 28.473(0.261) and 33.052(0.478). And the sum of the estimated GARCH parameters *($\alpha+\beta$)* is close to one for a model which ignores sudden changes compared to the model that incorporated the sudden change constraints. GARCH parameters *($\alpha+\beta$)* close to the one indicate that the changes in variance have a permanent impact on volatility (Wang & Moore, 2009).

The own volatility spillovers for the three capital markets are positive and significant. While own volatility spillovers indicate a one-way linkage between current volatility in the same market (domestic market) and past volatility shocks, the cross-volatility spillover signifies the one-way linkage between previous volatility in the domestic market and the present volatility in another market. (Natarajan, Singh, & Priya, 2014). For both models, the coefficient of the estimated parameters shown in Table 6 reveals that the own volatility spillover effects are higher than the cross-market spillover effects.

This shows that the market's domestic activities are more important in explaining volatility than the foreign markets. However, for some indexes, the magnitude of inter markets linkages is low and statistically significant. This shows that some of the European capital markets are not strongly integrated. While some markets' interrelationship is positive, others indicate a negative relationship.

Table 5. Comparison of volatility persistence among CAC-40, DAX-30, and FTSE-100

Stock Indexes	Volatility Persistence		Persistence decline
	Ignoring volatility changes	Controlling volatility changes	
French CAC 40	0.965	0.731	0.234
German DAX 30	0.907	0.801	0.106
The UK. FTSE 100	0.783	0.564	0.219

To validate the results from the two competing models, thus examining the essence of considering controlling sudden changes in variance by investors and policymakers, the likelihood ratio statistic (LR) for the two competing models is computed. The test is calculated thus, LR=2[($L\theta_1$)-$L(\theta_0)$] where $L(\theta_1)$ is the value of the maximum loglikelihood from the multivariate BEKK-GARCH model with control sudden changes. $L(\theta_0)$ indicates the loglikelihood value from the BEKK-GARCH model ignoring sudden changes. Therefore, $L(\theta_1)$=-5877.847 and $L(\theta_0)$= -5975.795. Thus, LR=195.896, and the test statistic is χ^2 distributed with a degree of freedom equal to the number of parameter restrictions from the model with sudden changes to the model without sudden changes. Specifically, the degree of freedom is the value found from the difference by the maximization over the entire space and after imposing some constraint. Hence, the critical values (P=0.1) = 85.527, (P=0.05) = 90.531, and (P=0.01) = 100.425. The null hypothesis of no variance change between the two models (with and without sudden changes) is rejected at 1%, 5%, and 10% significant levels. In other words, the controlled model fits the data significantly better, and the parameter constraint is significantly meaningful.

CONCLUSION

This research paper investigates sudden changes in volatility for three major European stock markets - French CAC 40, German DAX 30, and Britain's FTSE 100 stock, using the iterated cumulative sums of squares (ICSS) algorithm for the period 1994 – 2020. Besides capturing the simultaneous shifts in financial markets, the multivariate (trivariate) GARCH model framework shows to estimate and predict numerous markets spillover effects when volatility shifts are incorporated into the model, compared to the use of a univariate model such as Adesina (2017), Vivian & Wohar (2012).

Sudden change in the conditional variances in the three major European capital indexes showed to be largely explained by global events. For example, shifts in conditional variances of French CAC 40, German DAX 30 and the British FTSE 100 correspond to the periods of the early 2000s recession and the global financial crisis. These research paper findings are consistent with some previous research such as Kumar & Maheswaran (2012); Ewing & Malik (2005); Wang & Moore (2009) etc. who argued that sudden shifts in variance are mainly caused by global financial events. In addition, this research paper reveals that volatility persistence decreases when volatility changes are controlled compared to ignoring it. Therefore, controlling information about sudden changes in variance enhances the accuracy of estimating volatility. However, this position is quite different from Vivian & Wohar (2012) who argued that volatility persistence remains high for many stock returns even when the sudden change effects are accounted for or controlled, and for Dong & Yoon, (2018) paper showed that sudden shift reduces the degree of volatility persistence respectively.

To obtain a good estimate of the financial market's volatility persistence, this paper has shown the need to account for sudden changes in variance. The implication of this suggests that many existing research papers on volatility persistence which never accounted for the shift in variance may have generated a biased result that might have been overestimated or underestimated. The Stock market is one of the major indicators of the overall health condition of a country's economy. Therefore, a bias and wrong forecast about market volatility can mislead relevant government agencies into taking a wrong decision on a crucial matter concerning the economy. Besides, the hedge fund manager needs precise and accurate market information for an investment strategy to take risky management decisions. For these reasons, Fakhfekh, Hachicha, Jawadi, Selmi, & Cheffou, (2016) posited that understanding volatility measurement is crucial in monetary policies, investment decisions, pricing, risk management, and banking security valuation, etc. Therefore, government agencies, investors as well as hedge managers in Germany, France, and the United Kingdom must understand that relying on volatility forecast results that never accounted for the sudden change is highly risky. Controlling the joint effects of sudden change reduces or eliminates the volatility transmission. (Nguyen, Chaiechi, Eagle, & Low, (2020)

The own markets volatility coefficient showed to be higher than the cross-market spillover effects. This conforms to previous papers such as Yousaf, Ali, &Wong (2020). This suggests that domestic activities for the three markets are more crucial in explaining market volatility than foreign markets. And that volatility persistence declines when volatility changes are controlled. For future research, this paper suggests the application of a multivariate GARCH model to re-examine previous studies that have employed the univariate GARCH model to estimate the multiple volatility persistence of related financial market variables.

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APPENDIX I

Table 6. Estimation of VAR-BEKK-GARCH(1,1) model parameters

Variables	Ignoring sudden changes				Controlling sudden changes			
	Coeff	**St. Err**	**T. Stat.**	**Signif.**	**Coeff**	**St. Err**	**T. Stat.**	**Signif.**
Mean(1,1)	0.107	0.068	1.562	0.118	0.028	0.045	0.621	0.534
Mean(2,2)	-0.197	0.074	-2.670	0.007	-0.098	0.050	-1.945	0.051
Mean(3,3)	0.050	0.047	1.058	0.289	-0.001	0.047	-0.022	0.981
C(1,1)	22.421	3.768	5.951	0.000	80.253	26.200	3.063	0.002
C(2,1)	9.940	10.903	0.912	0.362	101.194	25.742	3.931	0.000
C(2,2)	20.348	9.638	2.111	0.035	23.100	17.356	1.331	0.183
C(3,1)	8.568	4.851	1.766	0.077	46.858	18.309	2.559	0.010
C(3,2)	-7.897	5.847	-1.351	0.177	125.572	29.187	4.302	0.000
C(3,3)	0.001	9.155	0.000	1.000	18.486	10.941	1.690	0.091
A(1,1)	0.072	0.021	12.787	0.000	0.065	0.068	-0.951	0.342
A(1,2)	-0.117	0.020	-5.791	0.000	-0.410	0.127	-3.213	0.001
A(1,3)	0.163	0.025	6.600	0.000	0.174	0.024	7.119	0.000
A(2,1)	0.028	0.009	3.083	0.002	0.088	0.028	3.167	0.002
A(2,2)	0.004	0.019	16.548	0.000	0.203	0.062	3.271	0.001
A(2,3)	-0.086	0.018	-4.775	0.000	-0.061	0.017	-3.613	0.000
A(3,1)	0.272	0.025	10.783	0.000	0.363	0.051	7.057	0.000
A(3,2)	0.646	0.057	11.372	0.000	0.615	0.089	6.935	0.000
A(3,3)	0.021	0.028	18.422	0.000	0.410	0.039	15.475	0.000
B(1,1)	0.962	0.015	62.948	0.000	0.668	0.063	10.540	0.000
B(1,2)	0.117	0.030	3.858	0.000	-0.031	0.058	-0.526	0.599
B(1,3)	-0.069	0.010	-6.691	0.000	-0.138	0.060	-2.292	0.022
B(2,1)	-0.026	0.009	-2.893	0.004	0.006	0.011	0.513	0.608
B(2,2)	0.902	0.016	56.503	0.000	0.489	0.073	6.661	0.000
B(2,3)	0.037	0.007	5.205	0.000	0.128	0.035	3.653	0.000
B(3,1)	-0.067	0.008	-8.636	0.000	-0.269	0.054	-4.951	0.000
B(3,2)	-0.219	0.015	-14.495	0.000	0.035	0.107	0.332	0.739
B(3,3)	0.884	0.012	76.320	0.000	0.240	0.067	3.546	0.000

Note:

1. *Source: RATS 10.0 output.*
2. **, ** and *** indicates 10%, 5% and 1% significance respectively*
3. *1, 2, 3 indicate CAC-40, DAX-30 and FTSE-100 indexes respectively.*
4. *For brevity, the controlled sudden change dummies were removed*

PREISPITIVANJE IZNENADNIH PROMENA I POSTOJANJE VOLATILNOSTI NA EVROPSKIM TRŽIŠTIMA KAPITALA: NEKI EMPIRIJSKI DOKAZI

Rezime:

Razumevanje ponašanja tržišne volatilnosti je ključno za određivanje cena imovine, izbor portfelja, upravljanje rizikom i strategije trgovanja. Standardni model generalizovane autoregresivne uslovne heteroskedastičnosti (GARCH) pretpostavlja da nema promene u varijansi, otuda njegova nesposobnost da proizvede dobru procenu postojanosti promenljivosti. Stoga, ovaj istraživački rad preispituje postojanost volatilnosti, kao i iznenadne promene u varijansama za neka velika evropska tržišta kapitala – francuski CAC 40, nemački DAKS 30 i britanski FTSE 100. Studija obuhvata istovremene promene u varijansi, detektovane algoritmom iteriranih kumulativnih suma kvadrata (ICSS), inkorporiranih u multivarijantni BEKK-GARCH model. Dobijene informacije pokazuju da otkrivene promene odgovaraju kako globalnim tako i domaćim dešavanjima. Rezultati su takođe pokazali da je postojanost volatilnosti smanjena u modelu promene kontrolisane volatilnosti u poređenju sa modelom koji zanemaruje promene volatilnosti. Implikacija ovih rezultata ukazuje da su prethodne studije o postojanosti evropske nestabilnosti možda prikazale prekomerne rezultate.

Ključne reči:
postojanost volatilnosti,
iznenadna promena,
pomeranje varijanse,
ICSS algoritam,
berza.