MAKÜ | Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty

e-ISSN: 2149-1658
Volume: 11 / Issue: 1
March, 2024
pp.: 134-152

Heterogeneous Market Hypothesis in Major European Stock Exchanges

Aykut KARAKAYA[1], Melih KUTLU[2]

1. Assist. Prof. Dr.,
Recep Tayyip Erdoğan University,
aykut.karakaya@erdogan.edu.tr,
https://orcid.org/0000-0001-6491-132X

2. Assist. Prof. Dr.,
Samsun University,
melih.kutlu@samsun.edu.tr,
https://orcid.org/0000-0002-8634-6330

https://doi.org/10.30798/makuiibf.1220275

Abstract

The aim of this study is to investigate heterogeneous market efficiency in European stock exchanges using Augmented HAR-RV model. According to the heterogeneous market efficiency hypothesis, investors create portfolios according to different time horizons and different market situations may arise in the reflection of information on price. We find evidence of the validity of the heterogeneous market efficiency model in European stock exchanges. Investors interpret information differently at different time horizons. Medium- and long-term investment decisions are a major influence. These results help explain the volatility that may occur in different time horizons. Portfolio diversification should also be made according to different investments in different horizons. Short-term global volatility shock has been effective on European stock markets.

Keywords: Heterogeneous Market Hypothesis, European Stock Exchanges, Realized Volatility, HAR Model.

Article Type	Application Date	Acceptance Date
Research Article	December 16, 2022	February 7, 2024

To cite this article: Karakaya, A. & Kutlu, M. (2024). Heterogeneous Market Hypothesis in Major European Stock Exchanges. *Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty, 11*(1), 134-152. https://doi.org/10.30798/makuiibf.1220275

1. INTRODUCTION

Change is inevitable in many economic and social issues where change and development are continuous. Because of the change, the field of finance also develops itself because of the level of existing needs and additional needs that arise. These developments have shaped modern finance from the mid-20th century to the present. Especially with the discovery of globalization and technology, the increase in the acceleration of this development in modern finance in the 21st century has become dazzling.

Market efficiency is more about price than portfolio selection and belief. This definition is an intrinsic value-oriented definition. It can also be said that market efficiency is directly concerned with price behavior, and indirectly with portfolio selection and belief (Beaver, 1981: 29). Market efficiency is important for all real and financial markets. The efficiency of stock markets is important in macro and micro aspects. Market efficiency at the micro-level shows that the prices formed in this market and the transactions made in line with these prices are fair. Thus, investors will have confidence in the market. Market efficiency at the macro level will cause an increase in the supply and demand to the market, based on confidence. As a result, it will realize the economic functions expected from the stock market.

The fact that investors have different time horizons creates a heterogeneous structure. How does volatility caused by heterogeneous structure affect market efficiency? In the efficient markets hypothesis, investors have homogeneous expectations and liquidity is ignored. Realizedly, investors may also differ in their perception of the market. Since there is a differentiation in the studies conducted within the framework of the Heterogeneous Market Hypothesis (HPH) and therefore these situations cannot be explained through traditional models, studies have been conducted with new models based on the heterogeneous market hypothesis (Tao et al., 2018; Cheong, 2013; Buncic and Gisler, 2016). Especially, a fat tail of financial data is a common occurrence. This means that very high or low volatility levels can be seen. Volatility lag values that have long memory are determined. Therefore, volatilities are realized over differing interval sizes (daily, weekly, monthly) in HAR models. Whether an investor is individual or corporate can also change the perception of the market. Markets become stable as investors are provide liquidity to the market.

The aim of this study is to investigate heterogeneous market efficiency in major European Stock Market. High frequency realized volatility of Europe's leading stock markets has analyzed with the Heteroscedastic Autoregressive-Realized Volatility model. According to the result of this heterogeneous analysis method, the validity of the Heterogeneous Market Hypothesis (HMH) tested in European stock markets. In this direction, HMH in local markets examine in the first stage. HMH tests in the EURO STOXX50, FTSE100 (UK), DAX (Germany), CAC40 (France), IBEX (Spain), MIB (Italy), and AEX (Nederland) indexes. HMH of the global market on local markets test with the augmented HAR model in which the VIX index include. Financial markets in Europe are among the oldest and well-established markets. Therefore, it is suitable for market efficiency research and testing the heterogeneous structure where investors have different trading times in these markets. It is more accurate to analyze the investor this way in developed markets. These countries are both developed and commercially close countries. There are both regional and global investors in these stock markets. Sufficient depth and breadth are also available in these markets.

In the second part of the study, we will describe the theoretical framework of market efficiency in its developing structure. In the third chapter, the literature review, studies on market efficiency, especially in European markets examine. After the data and method section, the findings presented.

2. MARKET EFFICIENCY

Market efficiency is in two groups as operational efficiency and information (price) efficiency. Operational efficiency is internal, and information efficiency is external. In a market with operational efficiency, transaction costs are lower. It can define information efficiency as prices reflecting all available information. In an information-efficient market, additional information required for price, security-related supply and demand adjustments quickly transfer (Fabozzi et al., 2014: 294-295). Operational efficiency covers the economics of scale and pure inefficiency. Pure inefficiency divides into technical and allocative (Allen and Rai, 1996: 656). In the current technology in technical efficiency, it depends on providing maximum output with a certain input composition or producing a certain output combination using minimum input. Allocation efficiency is the ability to use input at the most appropriate rate, considering costs. Operational and allocation efficiency attributed to transaction costs and low trading price margin. The theoretical framework of the Efficient Markets Hypothesis (EMH), Fractal Markets Hypothesis (FMH), Adaptive Markets Hypothesis (AMH) and Heterogeneous Markets Hypothesis (HMH) examined below in terms of information efficiency.

The price can change when interest rates change or a situation with the company changes. When the price becomes high or low, a trading opportunity arises. Here, compliance of the prices with the news and the status of the price reflecting the information are important (Saunders and Cornett, 2015: 264). Many studies have contributed to the development of the efficient market hypothesis (Samuelson, 1965; Fama, 1965a; Fama, 1965b; Fama, 1970; Fama, 1991; Rubinstein, 1975; Zuckerman, 2012). Prior to these, there are preliminary studies on the estimation and random movement of prices (Cowles, 1933); Cowles, 1944); Cowles, 1960); Kendall, 1953).

The Fractal Market Hypothesis suggests that EMH is insufficient in terms of liquidity. The Fractal Market Hypothesis (FMH) suggestion that the reflection of shock on price varies according to the investor's investment horizon (Peters, 1994: 42).

Human is sometimes rational and sometimes irrational, and these are biological beings whose characteristics and behavior shape by the forces of evolution. The Adaptive Markets Hypothesis (AMH) is a new version of EMH derived from evolutionary principles. Prices reflect information put forward by environmental conditions and the number and nature of species in the economy (ecology) (Lo, 2004:

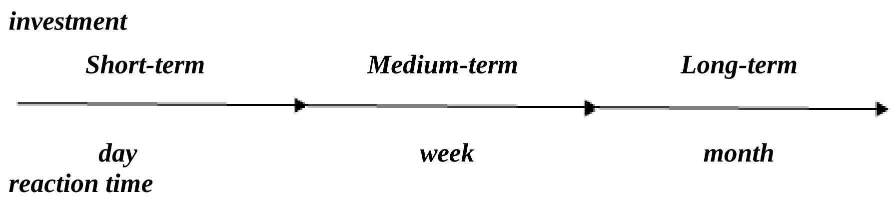
23; Lo, 2005:11; Lo, 2017: 188). Market efficiency is not a stable situation and depends on changes in investors (Dhankar, 2019: 298).

The volatility in equilibrium stock prices increases before it discloses public information, which is because of speculative behavior with heterogeneous information. This is a driving force for the efficient price system (Kwon and Park, 1986: 13). Volatility should negatively correlate with market presence and activity. different investors are likely to settle for different prices and decide to conduct their transactions in different market situations in a heterogeneous market. This situation creates volatility (Müller et al., 1993: 12). Short-term investors that produce volatility prevent long-term investors from entering the market (LeBaron, 2001: 248). Asymmetric information exists between short-term and long-term investors. When the volatility cluster increases, short-term investments respond to it, while long-term investors do not. Long-term investors and short-term investors use fundamental analysis and technical analysis, respectively (Müller, et al., 1997: 236).

There are market makers at the farthest point of the short-term side and central banks at the farthest point of the long-term side.

Time in the market is uncertain. Because the perception of time is different among investors. This is interaction between dynamics occurs. When interest rates and exchange rates change, the trend changes and this interaction forms the main structure of the volatility cluster. (Dacorogna et al., 2001: 199). The common behavior of all investors drives the market. Geographical location and working hours are also effective in this case (Dacorogna et al., 1995: 402). The reaction of heterogeneous participants at different time scales are shown in Figure 1.

Figure 1. Heterogeneous participants react over different time scales



Source: created by the authors, adapted from Cheong (2013)

Each component has its own time horizon and response time to news, depending on the characteristic frequency of action. Assuming that the volatility memory of a component decreases exponentially with a certain time constant (as in a GARCH (1,1) operation), the memory of the entire market comprises many such exponential declines with different time constants (Müller et al., 1993: 12). GARCH model cannot calculate the sophisticate volatility (Lux (2008), Wei and Wang (2008)). Corsi (2009), focuses on the heterogeneity that originates from the different time horizons. Based on the HMH, Corsi (2009) offer the HAR-RV model. In the heterogeneous market structure, responses to shocks in different periods create different volatility structures. These different volatilities create long-term dependence and heterogeneous market volatility (Cheong, 2013:249). Short-term investors use higher frequency data and have shorter memory than long-term investors. Therefore, the volatility perceived by short- and long-term investors differs from each other. This makes the concept of time important in measuring volatility (McMillan and Speight, 2006:115).

3. LITERATURE REVIEW

The efficient markets hypothesis has found a wide range of study in finance literature, and there are studies that test the validity of this theory. Grossman and Stiglitz (1980), in their study of market efficiency in terms of information, concluded that if the knowledge is cheap and accurate, the knowlodge can represent in the price, but because the information is expensive, prices do not reflect the information completely. Because they may not get the return, you pay for the information. Besides the reflection of information on the price, the behavior of the market is also important in terms of efficiency. De Bondt and Thaler (1985), in their study with stocks in the NYSE between January 1926 and December 1982, concluded that the market was overreact (against unexpected events) and the effectiveness was invalid in weak form. Lo and Mackinlay (1988) rejected the random walk hypothesis in their study of NYSE-AMEX market return between 1962 and 1985.

Chan et al. (1997) tested weak form efficiency in eighteen countries using unit root tests, and weak form efficiency detection in all countries individually. Worthington and Higgs (2004) tested market efficiency in 20 European markets, with daily data between 1988 and 2003. Unit root tests, serial correlation coefficient, run test and VRSs are use in the study. Test results support weak-form efficiency in emerging markets, but not in developed countries in Europe.

Liu et al. (1997) investigated market efficiency in Shanghai and Shenzhen stock exchanges between 1992 and 1995 by cointegration and causality analysis methods with daily data. The random walk hypothesis accepts within both markets. Narayan and Smyth (2004) tested the efficient markets hypothesis with monthly data between 1981 and 2003 in the Korean Stock Exchange (KSE KOSPI) using the unit root tests of Zivot and Andrews and Lumsdaine and Papell. In the period, efficient markets hypothesis is valid in KSE-KOSPI. Munir and Mansur (2009) tested the efficient markets hypothesis between 1980 and 2008 using the threshold auto regression with a unit root test at the Kuala Lumpur Stock Exchange (KLCI) and concluded that the efficient markets hypothesis is valid for KLCI. Alexeev and Tapon (2011), in their research on the Toronto stock market, found weak market activity in the period between 1980 and 2010. Model-based bootstrap and EGARCH models used. In a sectoral research, it’s conclude that some sectors are less effective.

Lynch and Zumbach (2003) investigated the correlations between historical volatility and realized volatility in the period from 1989 to 2001 using exchange rates, gold bullion market, DJIA, and the Swiss Market Index (SMI). Correlations show that the market is heterogeneous, with intra-day, daily, weekly and monthly data. Davies and Studnicka (2018) research heterogeneous impact of Brexit on the FTSE. They use CAR model on firms listed on London Stock Exchange. There is heterogeneity in the changes in firm expectations after Brexit, and this heterogeneity explained by the global value chain. The market reaction is consistent with investors responding to the potential effects on a firm's global value chain. Lee et al. (2014) tested the EMH with heterogeneous panel unit root test in international data set. Sixty stock markets across different income groups and regions research. Stock prices cannot be predicted based on past price movements.

Tao et al. (2018) tested the heterogeneous market hypothesis with HAR-type models and ARFIMA-type models in SSEC (26, July 1999 to 30, May 2014) and S&P500 (January 2, 1996 to June 24, 2013) indexes. They use intraday high-frequency data. Estimation coefficients have a significant positive relationship with the future multifractal volatility. Cheong (2013) tested heterogeneous market hypothesis in the S&P 500 index between 2005 and 2009, using Heterogeneous Autoregressive GARCH (HAR-GARCH) and ARFIMA models. The realized volatility models outperformed the inter-day data models for different frequency data. Cheong, et al. (2016) tested heterogeneous market hypothesis by using models based on autoregressive HAR model specifications in the BOVESPA index. Empirical findings are supporting the heterogeneous market hypothesis. Buncic and Gisler (2016) investigated volatility spillover among eighteen global stock markets using the HAR model. Data is between 2000 and 2015. According to the findings, volatility spillover from the US stock market to Australia and all European countries is important. Volatility in the US stock market at the weekly frequency negatively and significantly affects the other seventeen countries. Volatility in the US stock market at the monthly frequency negatively and significantly affects twelve of the other seventeen countries. Volatility spillover is stronger at lower frequencies.

When the literature is examined, the number of studies on HAR-type models that take into account the heterogeneous structure of investors is increasing day by day. In this study, we aim to contribute to the literature by investigating the heterogeneity in the major stock markets of Europe, which has not been adequately researched in the literature, and by representing policy recommendations within the framework of empirical findings.

4. DATA AND METHODOLOGY

The study data set is the realized volatility calculated in 5-minutes intraday intervals from January 1, 2010 to December 31, 2020. Realized volatility data consisted of 2830 observations daily. The number of stock indexes of European stock markets whose realized volatility is examined is seven. These are FTSE100 index (United Kingdom), DAX index (Germany), CAC 40 index (France), FTESE MIB index (Italy), IBEX 35 index (Spain), AEX index (Nederland) and Euro Stoxx 50 index. The VIX index included in the data set of the study in order to address the effect of global volatility on European stock markets. In the literature, the VIX index is used as a more comprehensive volatility indicator than other global volatility indicators (such as DJIA, Nasdaq 100 and S&P 500). The daily realized volatilities in European stock exchanges in the study data set obtained from the library of the Oxford-Man Institute's

Quantitative Finance Realized Library (https://realized.oxford-man.ox.ac.uk/data). Chicago Board Options Exchange Volatility Index (VIX) index data obtained from is the Federal Reserve Bank of St. Louis corporate web address (https://alfred.stlouisfed.org). Brief information about the indexes in the study is presented below. VIX measures volatility expectation in S&P 500 index. The VIX, which was started to be calculated in 1993, was first used to calculate the expected volatility of the S&P 100 index. Since 2003, it has been used to calculate the expected volatility of the S&P 500 index. The VIX has been an index used to measure the implied volatility of the market. VIX is closely monitored as a risk and uncertainty factor not only for the United States but also for the financial markets of all countries in the world.

The most commonly used methods of volatility measurement are historical volatility, extreme value volatility, and realized volatility (RV). The concept of RV has been proposed by Merton (1980). RV is a measure of volatility obtained by calculating the sum of the return squares of an asset between equally short time intervals in a day, such as 5, 10, or 15 minutes. The RV is expressed in equation (1) below:

$$\boldsymbol{RV_t = \sum_{i=1}^{m} r_{t,i}^2\,, t = 1, \dots, T} \tag{1}$$

$r_{t,i}$ is the intraday log-price difference $(100 \times \log(p_{t,i}) - \log(p_{t,i-1}))$. Returns observed for equally short periods i within the total time interval m per day at time t. The RV is obtained in $\sqrt{RV_t}$. Thus, high-frequency data allow modeling of the observed portion of volatility instead of an unobserved latent variable (such as ARCH or GARCH Engle (1982) and Bollerslev (1986)) or latent stochastic volatility (Taylor (1994) or Harvey (2013)) in the volatility model. In such a model proposed for observed RV, it is a heterogeneous autoregressive model.

Firstly, unit root test of RV series. Despite the possibility of spurious regression in the analysis of time series, we desire it that the series is stationary. There are time series unit root tests developed for this. The most widely used of these unit root tests are Dickey and Fuller (DF, 1979) Test, Augmented Dickey-Fuller (Dickey and Fuller, 1981) Test (ADF), Phillips and Perron (1988) Test (PP) and Kwiatkowski et al. (1992) Tests (KPSS). Zivot and Andrews (1992) is used as the structural break unit root test. The stationarity of the financial time series, which are the subject of this study, analyzed through ADF (1981) test, PP (1981) test, KPSS (1992) test and Zivot and Andrews (1992) test.

To eliminate the autocorrelation problem in ADF (1981) test, since the lag lengths of the dependent variable are included in the model, this causes the degree of freedom to decrease. In PP (1988) test, a nonparametric correction is made to the t test instead of adding the lags of the dependent variable to the model. In this way, the loss of degrees of freedom is eliminated. In ADF and PP unit root tests, the H_0 hypothesis states that the analyzed series is unit root, it is not stationary. The test statistics used in ADF (1981) and PP (1988) tests are based on McKinnon critical values. The time series examined in the unit root test developed by KPSS (1992) is free from trend. Therefore, the fact that the H_0 hypothesis cannot be rejected indicates that the analyzed series is trend stationary. The test statistic used in the KPSS (1992) test is an LM test based on residuals. In the Zivot ve Andrews (1992) test, the main hypothesis is unit root and the alternative hypothesis is trend stationarity. Three models are used: Model A, which allows a single break in the level, Model B, which allows a single break in the slope, and Model C, which allows a single break in both the slope and the level in the Zivot-Andrews (1992) unit root test,. Model A and C are used in this study.

In the literature, autocorrelation and partial autocorrelation coefficients are widely used to determine the long memory in financial time series. High coefficients considered as an indicator of dependency in the series. Tests developed to measure the level of dependency in the series according to autocorrelation and partial autocorrelation. Ljung and Box (1978) Q Statistics based on autocorrelation and partial autocorrelations calculated after unit root tests of the examined indexes. Because of the Ljung-Box (1978) Q Test, the existence of linear dependence in indexes tested. In the Ljung-Box (1978) Q Test, the H_0 hypothesis tested the index is linearly independent. Because of the test, if H_0 is reject, the index considered being linearly dependent distributed. Thus, it concluded that the index is auto-correlated and has a long memory feature. This result makes it necessary to analyze the indexes with methods that consider dependency (long memory). The HAR model takes this dependency into account.

RV analyzes classified under the following three groups in the applied literature. The first of these is the traditional ARMA or fractionally integrated ARMA (ARFIMA) class models in which long-term memory analyzes performed. Second, they are patterns of structural breaks or regime switches in the class of nonlinear time series analyzes. The third is heterogeneous autoregressive (HAR) models. In this study, RV analyzed by heterogeneous autoregressive (HAR) models in the third group.

HAR-RV, proposed by Corsi (2009), is a regression model in which volatility predict with the help of past heterogeneous volatilities. The volatility in the model has three different time horizons structure. Therefore, the model called HAR (3)-RV. This volatility structure in the past has been in daily, weekly and monthly format. It shows that today's volatility based not only on the volatility of the day before, but also on the volatility of the past week and last month. Thus, the volatility estimated by the model is less affected by excessive observations. It represents daily short-term volatility, weekly medium-term volatility and monthly long-term volatility. Also, long-term memory considered in the model. HAR (3)-RV structure of a particular stock market index give in equation (2) below (Corsi, 2009: 181):

$$\boldsymbol{RV_{t+1} = \beta_0 + \beta^d RV_t^d + \beta^w RV_t^w + \beta^m RV_t^m + \varepsilon_{t+1}} \tag{2}$$

The HAR formula of the RV of the stock market index given by $RV_t^d = RV_t$, $RV_t^w = \frac{1}{5}\sum_{i=1}^{5} RV_{t+1-i}$ and $RV_t^m = \frac{1}{22}\sum_{i=1}^{22} RV_{t+1-i}$. These represent the daily, weekly, and monthly HAR structure of the RV of the stock market index, respectively. These terms represent, representing short-, medium- and long-term volatilities in different time horizons.

It presents augmented HAR structure of a particular stock market index in equation (3) below (Buncic and Gisler, 2016: 1321):

$$\begin{gathered}\boldsymbol{RV_{t+1} = \beta_0 + \beta^d RV_t^d + \beta^w RV_t^w + \beta^m RV_t^m + \beta_{VIX}^d \log VIX_t^d} \\ \boldsymbol{+\beta_{VIX}^w \log VIX_t^w + \beta_{VIX}^m \log VIX_t^m + \varepsilon_{t+1}}\end{gathered} \quad \textbf{(3)}$$

In Equation (3), besides Equation (2), the volatility HAR structure of the VIX index representing global volatility included in the model. $\log VIX_t^d = \log VIX_t$, $\log VIX_t^w = \frac{1}{5}\sum_{i=1}^{5} \log VIX_{t+1-i}$ and $\log VIX_t^m = \frac{1}{22}\sum_{i=1}^{22} \log VIX_{t+1-i}$ denotes global heterogeneous volatility. These refer to the daily, weekly and monthly HAR structure of global volatility, respectively. These terms represent different time horizons in the model, representing short-, medium- and long-term volatilities.

5. EMPIRICAL RESULTS

The research results are presented under the headings below. First, time course graphical analysis of volatility in indexes is given. In the following titles, summary statistics, unit root test, autocorrelation test and finally augmented HAR-RV model estimation results are included.

5.1. Summary Statistics of Volatility

Summary statistics of the indexes presented in Table 1. The ranking of RV from high to low in terms of mean for the period examined realized as IBEX, STOXX50, MIB, CAC, DAX, FTSE and AEX. There is a similar ranking within the Median indicator. The finding is similar when looking at the maximum and minimum indicators. In terms of central trend indicators, the RV relatively higher in IBEX, STOXX50 and MIB stock market indexes. RV is low, especially in AEX and FTSE stock market indexes. According to the skewness and kurtosis measures of central tendency, it seen that the European stock market indexes do not have a normal distribution. Kurtosis values of the indexes revealed that the fat tail and the skewness values left-skewed. Especially the fat tail, i.e. leptokurtic distribution, shows that high RV experienced because of extreme movements and extreme values in European stock market indexes. Considering the central tendency and volatility indicators of the VIX index, we can say it has a normal distribution.

Table 1. Summary Statistics of RV and VIX Data

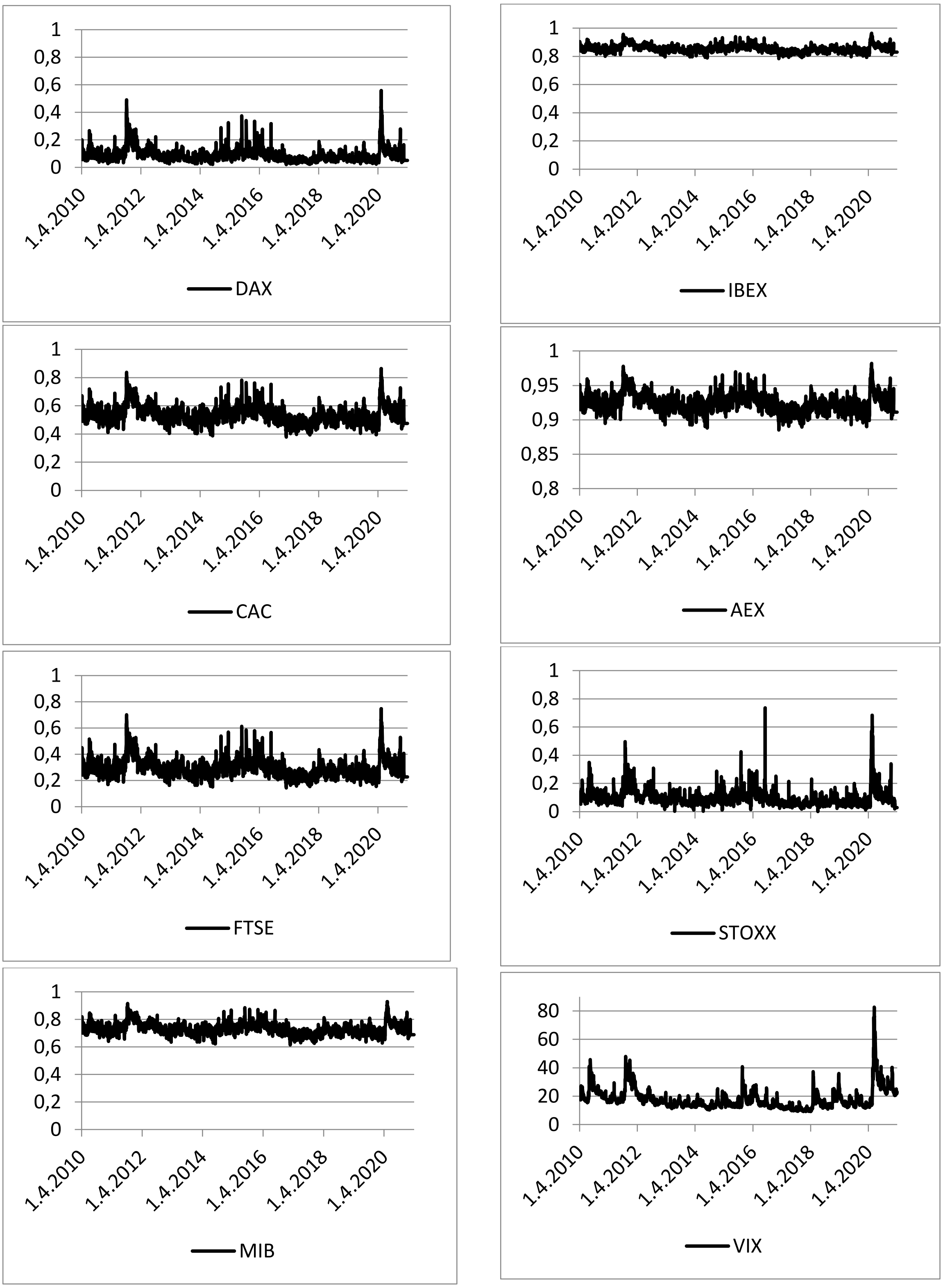
Indexes	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
RV_{AEX}	0.0084	0.0046	0.4200	0.0002	0.0187	12.5855	217.9575
RV_{CAC}	0.0109	0.0063	0.4362	0.0004	0.0199	10.1177	155.3262
RV_{DAX}	0.0105	0.0062	0.3118	0.0004	0.0175	7.85783	93.1794
RV_{FTSE}	0.0097	0.0049	0.6668	0.0001	0.0244	15.0173	324.9749
RV_{IBEX}	0.0153	0.0095	0.5510	0.0009	0.0244	9.9481	158.6063
RV_{MIB}	0.0119	0.0072	0.2728	0.0001	0.0174	6.3371	62.6730
$RV_{STOXX50}$	0.0127	0.0070	0.5405	0.0001	0.0256	10.7387	163.1350
VIX (log)	1.2265	1.2005	1.9174	0.9609	0.1459	0.9652	4.1388

5.2. Developments in Volatilities

Time path graphs of volatility of stock market indexes are presented in Graph 1 below. It observed that the volatility of the indexes changed over time. When the RVs in the European stock market indexes are evaluated collectively, it has been observed that the RVs have changed similarly in the long term. It remained high in the European stock markets as of the 2011, 2012, 2015, 2016, and 2020 periods of the RV. However, it fell in the European stock markets in the 2010, 2013, 2014, and 2017-2019 periods of the RV. Despite the parallelism experienced by the periods of the change of RVs, RV high in MIB, IBEX, AEX and CAC indexes. RV has low values in the FTSE, DAX and STOXX50 index. VIX increased in 2010, 2015, 2018, and 2020. The periods when volatility is low in the VIX are 2012, 2013-2014, 2016-2017, and 2019. Common periods of high volatility in Europe and VIX are 2015 and 2020. Common periods where it is low are 2013-2014, 2017, and 2019. Common movements in volatility stemmed from shocks on a global scale, not on a local or regional scale.

After the 2008 Global Financial Crisis, there are deteriorations in money markets. The credit contraction, which occurred as a result of a number of developments such as banks tightening lending conditions and reducing the functions of interbank markets, led to the emergence of imbalances in the macroeconomic and financial structures of European countries. It can be said that the 2011 and 2012 volatility clustering in the indices in Chart 1 is due to this debt crisis. The increase in volatility in the indices in 2016 is due to the Brexit referendum. It can be stated that the increase in 2020 was due to COVID-19 pandemic. VIX also reacted in the same periods.

Graph 1. Volatility Indexes



5.3. Unit Root Tests

The unit root test results of the RV series of the stock indexes of the stock exchanges reported in Table 2 below. We found it that the indexes do not contain unit roots. In the following analysis stages of the study, we should prefer methods that consider the stationary. In the study, estimation of RV series with steady-state processes performed by HAR analysis.

Table 2. Unit Root Tests Results

Indexes	ADF Test	PP Test	KPSS Test	Zivot-Andrews Test	
	t-Stat	Adj. t-Stat	LM-Stat	Model A	Model C
RV_{AEX}	-9.884***	-29.003***	0.152	-11.371*	-11.466**
RV_{CAC}	-11.151***	-26.948***	0.276	-10.755**	-10.877***
RV_{DAX}	-10.159***	-26.395***	0.275	-10.494**	-11.007**
RV_{FTSE}	-9.019***	-49.293***	0.223	-10.492**	-10.588**
RV_{IBEX}	-10.076***	-35.008***	0.334	-13.738***	-13.838***
RV_{MIB}	-8.985***	-32.550***	0.343	-11.766***	-12.040***
$RV_{STOXX50}$	-10.278***	-33.336***	0.217	-10.524**	-10.674***
VIX (log)	-5.715***	-5.452***	0.352	-6.868***	-7.425***

*, **, *** refers to significance levels of %10, 5%, and 1%, respectively. KPSS Asymptotic critical values are 0.739(%1), 0.463(%5) and 0.347(%10)

5.4. Dependence Test

Table 3 presents autocorrelation and heteroscedasticity test findings of the indexes. ACF, PACF and Ljung-Box statistics calculated for the first, fifth and twenty-second lags of the indexes. Ljung-Box Q statistics for European stock markets and VIX in Table 3 found to be statistically significant. H_0 hypothesis rejected for all the indexes. When autocorrelation and partial autocorrelations of the realized volatility of AEX, DAX, MIB and IBEX exchanges examined, it observed that they have long-term memory. Although the autocorrelation and partial autocorrelations of the realized volatility of STOXX50, FTSE and CAC exchanges are relatively low, it has determined that these exchanges also have long-term memory. In European stock exchanges, ACF (1) and ACF (5) values are above 0.50. Therefore, it observed that the volatility realized in the leading European stock markets in the period examined had a high persistence. Autocorrelations in VIX took values between 0.973 and 0.679. These very high autocorrelation coefficients showed the VIX index has a high level of volatility, ie high persistence. In addition, it showed that long-term memory (long memory) is strong in VIX. In line with this finding, volatility analysis in the study estimated with the HAR model, which considers long memory and heterogeneity.

Table 3. Dependence Test Results

Indexes	ACF(1)	ACF(5)	ACF(22)	PACF(1)	PACF(5)	PACF(22)	LB(1)	LB(5)	LB(22)
RV_{AEX}	0.711	0.501	0.091	0.711	0.017	0.014	1423.2**	5294.4**	8576.6**
RV_{CAC}	0.740	0.528	0.154	0.740	0.045	0.034	1540.0**	5571.1**	9635.9**
RV_{DAX}	0.751	0.542	0.210	0.751	0.127	0.016	1587.4**	5710.9**	10921**
RV_{FTSE}	0.469	0.422	0.104	0.469	0.121	0.012	618.52**	2718.6**	5419.2**
RV_{IBEX}	0.621	0.351	0.137	0.621	0.045	0.012	1085.3**	3081.5**	5240.9**
RV_{MIB}	0.690	0.482	0.227	0.690	0.074	0.011	1340.5**	4726.2**	9306.5**
$RV_{STOXX50}$	0.660	0.497	0.116	0.660	0.120	0.016	1225.2**	4347.7**	7269.4**
VIX (log)	0.973	0.872	0.679	0.973	0.033	0.029	2662.7**	12180**	40490**

* and ** refer to significance levels of 5%, and 1%, respectively

5.5. Augmented HAR Model Test Results

The results of the augmented HAR-RV (3) have used by equation (3), in which we model the volatility in the European stock market indexes, presented in Table 4 below. Model heteroscedasticity and autocorrelation consistent (HAC) calculated with the variance / covariance matrix estimator. In

Table 4, the dependent variable in volatility models is the expected RV of the stock market index. Independent variables are the past 1-day RV of the dependent variable, the average RV for the past 5 working days and the average RV for the past 22 working days. Thus, the effects of three different volatility structures on the European stock market indexes RVs intended to measure. In addition, in order to measure the effects of three different volatility structures of global volatility on the RVs of European stock exchanges indexes, the previous 1 weekday VIX (log) of the VIX index, the average VIX (log) of the past 5 weekdays and the average VIX (log) of the past 22 weekday included as independent variables in the model. Independent variables that show these three different time horizons in the model express short, medium and long-term volatility. Daily, weekly and monthly volatilities show the effects of short-term volatility, medium term volatility and long-term volatility, respectively. The three volatility structures in the model represent short, medium and long-term investors.

It seen that the augmented HAR model can explain 57% -71% of the change in European stock market indexes in Table 4. The order of explanation from lowest to highest is IBEX, FTSE 100, EUROSTOXX 50, MIB, CAC 40, AEX and DAX. The European stock market indexes IBEX and FTSE 100 have the lowest determination of both own and global volatility. The European stock exchange indexes where the determination of its own and global volatility is the highest are DAX, CAC 40 and AEX.

In Table 4, the second last term gives the statistical significance test of the VIX coefficients together (X^2_{VIX} Statistic). CAC 40 and Euro Stoxx 50 are significant at the 10% significance level. The last term is the test of the statistical significance of all coefficients in the RV model together (X^2_{RV} Statistic). These two tests are statistically significant. Thus, it has found that the European stock market indexes RVs have the property of time-dependent heteroscedasticity both in their own volatility shock and in the global volatility shock (VIX).

AEX expected RV affected by its own daily, weekly and monthly volatility shocks. In addition, daily and weekly global volatility shocks affected the AEX RV. CAC 40s weekly and monthly volatility shocks found effective on expected RV. The monthly global volatility shock CAC 40 affected the expected RV. DAX expected RV affected by its own weekly and monthly volatility shocks. DAX expected RV affected by daily, weekly and monthly levels of global volatility. The EUROSTOXX 50 expected RV affected by its weekly and monthly volatility shock. Weekly and monthly global volatility shocks affected EUROSTOXX 50 expected RV. The impact of all levels of FTSE 100 expected RV both self and global volatility shocks detected. IBEX's expected RV weekly and monthly volatility shocks effective. Weekly and monthly global volatility shocks affected IBEX's expected RV. The MIB expected RV affected by its own weekly and monthly volatility shocks. In addition, weekly and monthly global volatility shocks affected the RV expected to MIB.

The finding revealed in the model is that the expected RV coefficients in the European stock market indexes are negative, weekly RV coefficients are positive and monthly RV coefficients are negative again. On the other hand, the daily coefficients of global volatility to the expected RV in European stock markets found to be positive, weekly negative and monthly positive. This finding means that the effect of both local and global volatility on volatility in stock markets shows the characteristic of time-dependent heteroscedasticity. In addition to the volatility of the stock markets, its volatility decreases daily, increases it weekly and decreases again monthly. In global, the direction of the impact is opposite to the local.

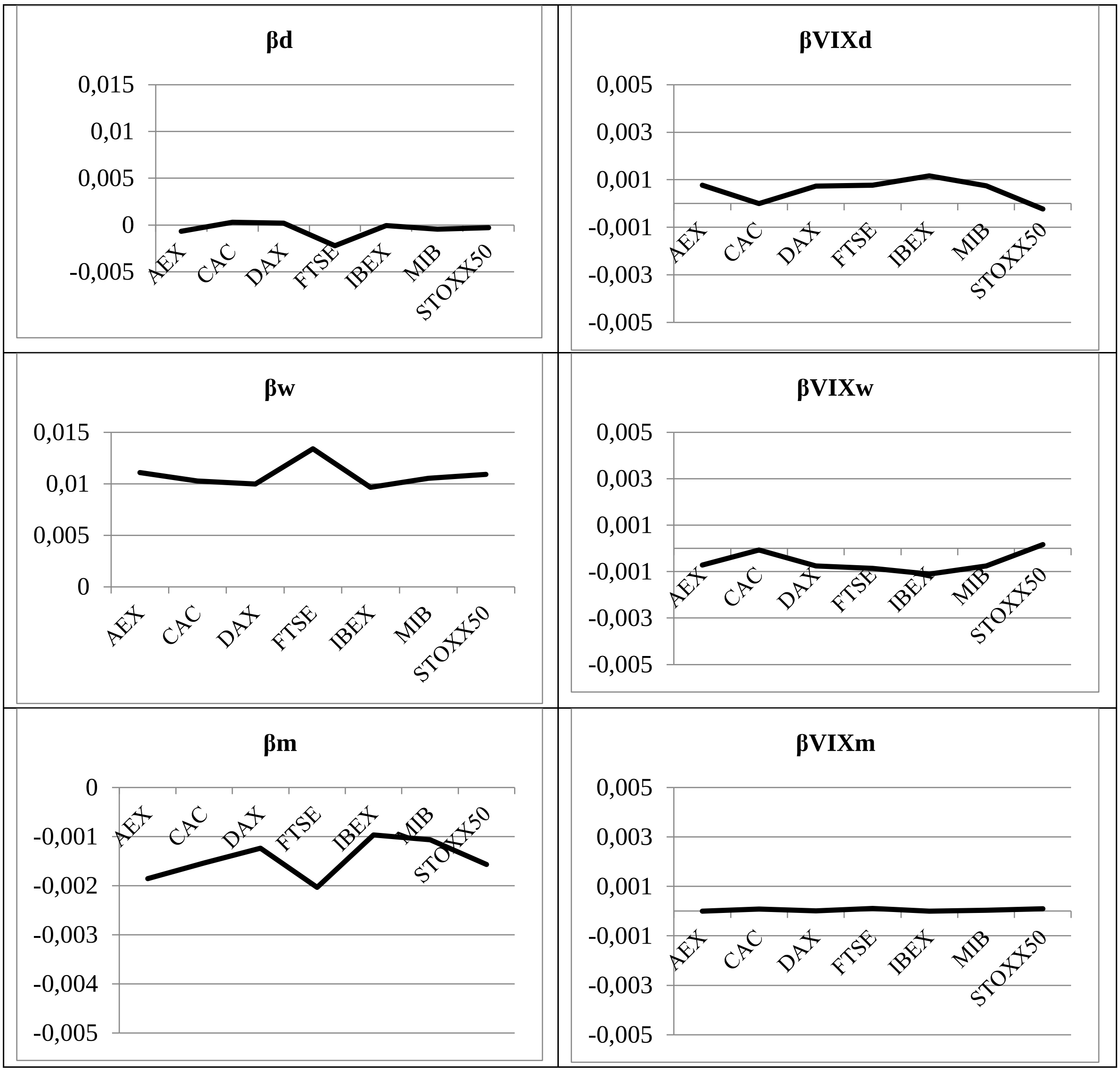
Table 4. Augmented HAR(3)-RV Model Results

	AEX	CAC40	DAX	EUROSTOXX50	FTSE100	IBEX	MIB
β_0	-0.000059 [0.000002]	-0.000244 [0.000016]	-0.000033 [0.000021]	-0.000022 [0.000017]	-0.000025 [0.000012]	-0.000048 [0.000023]	-0.000025 [0.000016]
β^d	-0.000685 [0.000307]	0.000299 [0.000519]	0.000199 [0.000788]	-0.000278 [0.001025]	-0.002203 [0.000237]	-0.000065 [0.000345]	-0.000434 [0.000670]
β^w	0.011077 [0.000662]	0.010268 [0.000738]	0.009988 [0.001123]	0.010903 [0.001241]	0.013401 [0.000675]	0.009666 [0.000646]	0.010531 [0.000776]
β^m	-0.001858 [0.000515]	-0.001535 [0.000528]	-0.001237 [0.000578]	-0.001568 [0.000495]	-0.002033 [0.000509]	-0.000966 [0.000332]	-0.001063 [0.000382]
β^d_{VIX}	0.000768 [0.000215]	0.000005 [0.000069]	0.000729 [0.000192]	-0.000223 [0.000128]	0.000773 [0.0002619	0.001164 [0.000449]	0.000748 [0.000208]
β^w_{VIX}	-0.000711 [0.000254]	-0.000065 [0.000099]	-0.000752 [0.000183]	0.000159 [0.000107]	-0.000857 [0.000297]	-0.001106 [0.000478]	-0.000753 [0.000237]
β^m_{VIX}	0.000002 [0.000008]	0.000088 [0.000051]	0.000006 [0.000003]	0.000095 [0.000046]	0.000112 [0.000055]	-0.000003 [0.000078]	0.000035 [0.000044]
R^2	0.705656	0.702028	0.712006	0.639572	0.584487	0.578633	0.667756
X^2_{VIX} Statistic	15.12543 [0.0000]	6.59444 [0.0860]	18.19253 [0.00004]	6.83298 [0.0774]	11.25661 [0.0104]	8.783381 [0.0323]	16.16247 [0.0011]
X^2_{RV} Statistic	2045.532 [0.0000]	4379.038 [0.0000]	2704.107 [0.0000]	3272.168 [0.0000]	7601.881 [0.0000]	5348.837 [0.0000]	2870.087 [0.0000]

Graph 2 presents the augmented HAR model parameter coefficients that show how the RV in the European stock market indexes affected. FTSE 100 expected RV negatively affected by daily volatility. The impact on the FTSE 100 has been significant. The expected RV of all indexes strongly positively affected by the weekly volatility. The volatility of the FTSE 100 was very high, while the volatility of other indices was high. The effect of monthly volatility is negative on the expected volatility of indices. The effect has been significant in FTSE 100, AEX and EUROSTOXX50. These findings suggest that the expected volatility of the FTSE 100 is higher than the short-term volatility for the long and medium term. It has determined that the effect of medium and long-term volatility on the expected volatility of AEX and EUROSTOXX50 is significant. The decisions of medium and long-term investors have been decisive in FTSE 100, AEX and EUROSTOXX50. In other indexes, the determinants of medium-term investors' behavior came to the fore. Medium-term and long-term volatility shocks effective in European stock markets. This finding is that long memory is valid.

Short-term global volatility (VIX) positively affected RVs in IBEX, MIB, DAX, FTSE100 and AEX. This effect does not apply to medium and long term global volatility. Therefore, the daily global volatility affected the European stock markets, weekly and monthly global volatilities do not affected the European stock markets. Short-term investors trading on European stock markets affected by global volatility. The decisions of investors making medium and long-term investments not affected by global volatility. It shown that global volatility does not have a long memory in European stock markets. Therefore, the short-term global volatility shock has been effective in European stock markets.

Graph 2. Plots of all parameters estimates from the augmented HAR model



6. CONCLUSION

The aim of this study is to test HPH validity in volatility in major European stock markets. Another aim of the study is the compatibility of the effect of global volatility on European stock market volatility with HPH. Seven European stock market indexes and VIX indexes have considered. Analysis method of the study is the HAR model, which tests long memory and HPH. Analysis results summarized below:

Volatility in European stock markets has changed. When evaluated collectively with the RVs in the European stock market indexes, the movement of the RVs has shown similarities in the long term.

Despite the parallelism experienced as of the periods in the change of RVs, RV is high in MIB, IBEX, AEX and CAC indexes. RV has low values in the FTSE, DAX and STOXX50 index.

Volatility in European stock markets increased in 2011-2012, 2015-2016 and 2020 periods. Volatility in European stock markets decreased in 2010, 2013-2014 and 2017-2019 periods. Volatility in the VIX index is high in 2010, 2012, 2015, 2018, and 2020. However, volatility in the VIX index is low in 2013-2014, 2016-2017, and 2019. Common periods of high volatility in Europe and VIX index are 2012, 2015, and 2020. Common periods where it is low are 2013-2014, 2017, and 2019. Common movements in volatility stemmed from shocks on a global scale, not on a local or regional scale.

It has determined that the volatility in the European stock market indexes does not have a fat tail and normal distribution. In addition, volatilities found to have a static process characteristic. Because of autocorrelation test, it found that volatility series have long memory. Based on these findings, it estimated the volatilities with the HAR model. According to the model findings, the most recent past information not supported in European stock markets, where it affects the expected volatility more. Investment decisions representing medium and long-term horizons had a significant impact on European stock markets. In particular, the influence of the medium-term investment horizon played a dominant role. Findings support the HPH. Similar results got with Tao et al. (2018) Cheong (2013) Cheong et al. (2016) and Buncic and Gisler (2016). Investors who have different investment time horizons in European stock exchanges interpret the market information differently. Short-term investors need a significant amount of cash soon. Medium investors take risks between low and high risk. Investments that want to earn high returns and involve a certain risk made by long-term investors. These differences in investor horizons affect the portfolio diversification of investors.

The findings show that European stock markets can better explain when alternative volatility structures created. In this way, it is possible to understand the long memory volatility behavior in European stock markets. This finding is important for investors in planning their portfolio strategy. It shows that market efficiency is worth researching. Long memory effect not observed in the effect of global volatility (VIX) on European stock markets in the model. Therefore, the short-term global volatility shock has been effective on European stock markets. According to Müller et al. (1997), different investor profiles in the markets cause different fluctuations to perceived and reacted according to this perception. The significant impact of the short-term global volatility shock on European stock markets shows that there are more investors who make higher-frequency evaluations and have short-term memory in these markets. Here, not only the investor profile but also the volatility structure divided into components transitory and permanent. Volatility is transitory to European stock markets. This result shows that investment reaction times are also short term.

The study carried out on important stock market indexes and global volatility index in Europe. It takes volatility and volatility transitions into account in the analysis. It should take these limitations into account when evaluating the results of the study. Despite these limitations, the study revealed that it revealed both the volatility structure in European stock markets and the effects of global volatility on the volatility of European stock markets. In future studies, it may take the effects of factors such as volume or liquidity on volatility into account.

The study does not necessitate Ethics Committee permission.

The study has been crafted in adherence to the principles of research and publication ethics.

The authors declare that there exists no financial conflict of interest involving any institution, organization, or individual(s) associated with the article. Furthermore, there are no conflicts of interest among the authors themselves.

The authors contributed equally to the entire process of the research.

REFERENCES

Alexeev, V. & Tapon, F. (2011). Testing weak form efficiency on the Toronto Stock Exchange. *Journal of Empirical Finance*, *18*(4), 661–691. https://doi.org/10.1016/j.jempfin.2011.05.002

Allen, L. & Rai A. (1996). Operational efficiency in banking: An international comparison, *Journal of Banking & Finance,* (20), 655-672. https://doi.org/10.1016/0378-4266(95)00026-7

Beaver, W. (1981). Market Efficiency. *The Accounting Review*, *56*(1), 23-37.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, (31), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Buncic, D. & Gisler, K. I. M. (2016). Global equity market volatility spillovers: A broader role for the United States. *International Journal of Forecasting*, (32), 1317–1339. https://doi.org/10.1016/j.ijforecast.2016.05.001

Chan, K.C., Gup, B.E. & Pan, M. S. (1997). International stock market efficiency & integration: A study of eighteen nations. *Journal of Business Finance & Accounting*, *24*(6), 803-813. https://doi.org/10.1111/1468-5957.00134

Cheong, C. W. (2013). The computational of stock market volatility from the perspective of heterogeneous market hypothesis. *Journal of Economic Computation & Economic Cybernetics Studies & Research*. *47*(2), 247-260.

Cheong, C. W., Cheng, L. M., & Yap, G.L.C. (2016). Heterogeneous market hypothesis evaluations using various jump-robust realized volatility. *Romanian Journal of Economic Forecasting*, *19*(4), 50-64.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, *7*(2), 74–196.

Cowles, A. (1933). Can stock market forecasters forecasts. *Econometrica*, *1*(3), 309-324. https://doi.org/10.2307/1907042

Cowles, A. (1944). Stock market forecasting. *Econometrica*, *12*(3/4), 206-214.

Cowles, A. (1960). A revision of previous conclusions regarding stock price behavior. *Econometrica*, *28*(4), 909-915. https://doi.org/10.2307/1907573

Dacorogna M.M, Müller U.A., Jost , C., Pictet, O.V., Olsen, R.B. & Ward, J.R. (1995). Heterogeneous real-time trading strategies in the foreign exchange market. *The European Journal of Finance*, (1), 383-405. https://doi.org/10.1080/13518479500000026

Dacorogna, M. M, Müller U., Olsen, R. & Pictet, O. (2001). Defining efficiency in heterogeneous markets. *Quantitative Finance*, *1*(2), 198-201. https://doi.org/10.1080/713665666

Davies, R.B. & Studnicka, Z. (2018). The heterogeneous impact of Brexit: Early indications from the FTSE. *European Economic Review*, (110), 1–17. https://doi.org/10.1016/j.euroecorev.2018.08.003

De Bondt, W. & Thaler, R. (1985). Does the stock market overreact? *Journal of Finance*, *40*(3), 793-805. https://doi.org/10.2307/2327804

Dhankar, R.S. (2019). *Risk-Return Relationship & Portfolio Management*. Springer.

Dickey, D.A. & Fuller, W.A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, *74*(366), 427- 431. https://doi.org/10.2307/2286348

Dickey, D. A. & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, (49), 1057–72.

Engle, R.F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, (50), 987–1007.

Grossman, S., & Stiglitz, J. (1980). On the impossibility of informationally efficient markets. *The American Economic Review*, *70*(3), 393-408.

Fabozzi, F.J., Modigliani, F. & Jones, F. J. (2014). *Foundations of financial markets & institutions*, 4th Edition, Pearson Education Limited.

Fama, E. (1965a). The behavior of stock-market prices. *The Journal of Business*, *38*(1), 34-105.

Fama, E. (1965b). Random walks in stock market prices. *Financial Analysts Journal*, *21*(5), 55-59.

Fama E. (1970). Efficient capital markets: A review of theory & empirical work. *Journal of Finance*, *25*(2), 383-417.

Fama E. (1991). Efficient capital markets: II. *Journal of Finance*. *46*(5), 1575-1617. https://doi.org/10.2307/2328565

Harvey, A.C., (2013). *Dynamic models for volatility & heavy tails, with application to financial & economic time series*. Cambridge University Press.

Kendall, M. (1953). The analysis of economic time-series-part I: Prices. J*ournal of the Royal Society*, *116*(1) 11- 34. https://doi.org/10.2307/2980947

Kwiatkowski, D., Phillips P.C.B., Schmidt P. & Shin Y., (1992). testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, (54), 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y

Kwon, Y. K. & Park H. Y. (1986). Heterogeneous information, market efficiency & the volatility of equilibrium stock prices. *Bureau of Economic & Business Research University of Illinois, Urbana-Champaign Working Paper*, (1220), 1-16.

LeBaron, B. (2001). Evolution & time horizons in an agent-based stock market. *Macroeconomic Dynamics*, (5), 225-254.

Lee, C.C., Tsong, C.C. & Lee, C.F. (2014). Testing for the efficient market hypothesis in stock prices. international evidence from nonlinear heterogeneous panels. *Macroeconomic Dynamics*, (18), 943–958.

Liu, X., Song, H. & Romilly, P. (1997). Are Chinese stock markets efficient? A cointegration & causality analysis. *Applied Economic Letters*, *4*(8), 511-515. https://doi.org/10.1080/758536636

Ljung, G. M. & Box, G. E. P. (1978). On a measure of a lack of fit in time series models. *Biometrika*, (65), 297-303. https://doi.org/10.2307/2335207

Lo, A. W. & MacKinlay, A.C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *Review of Financial Studies*, (1), 41– 66.

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management*, (30), 15– 29.

Lo, A. W. (2005). Reconciling efficient markets with behavioral finance: The adaptive markets hypothesis. *Journal of Investment Consulting*, (7), 21– 44.

Lo, A. W. (2017). *The adaptive markets: financial evolution at the speed of thought*, Princeton University Press.

Lux, T. (2008). The markov-switching multifractal model of asset returns. *Journal of Business & Economic Statistics*, *26*(2), 194–210. https://doi.org/10.1198/073500107000000403

Lynch, P. E. & Zumbach G. O. (2003). Market heterogeneities & the causal structure of volatility. *Quantitative Finance*, *3*(4), 320-331. https://doi.org/10.1088/1469-7688/3/4/308

McMillan, D. G. & Speight A.E. (2006). Volatility dynamics & heterogeneous markets, int. *J. Fin. Econ.*, (11), 115–121. https://doi.org/10.1002/ijfe.281

Merton, R. (1980). On estimating the expected return on the market: an exploratory investigation. *Journal of Financial Economics*, (8), 323–361. https://doi.org/10.1016/0304-405X(80)90007-0

Munir, Q. & Mansur, K. (2009): Is Malaysian stock market efficient? Evidence from threshold unit root tests. *Economics Bulletin*, *29*(2), 1359-1370.

Müller U.A., Dacorogna M.M., Dave, R.D., Pictet, O.V., Olsen, R.B. & Ward, J.R. (1993). *Fractals & intrinsic time: A challenge to econometricians*. Invited presentation at the XXXIXth lnternational AEA Conference on Real Time Econometrics, Research Report UAM.1993-08-16, Olsen & Associates, Zurich.

Müller U.A., Dacorogna M.M., Dave, R.D., Olsen, R.B., Pictet , O.V. & Weizsacker, J. E. (1997). Volatilities of different time resolutions-Analyzing the dynamics of market components. *Journal of Empirical Finance*, (4), 213-239. https://doi.org/10.1016/S0927-5398(97)00007-8

Narayan, P. K. & Smyth, R. (2004). Is South Korea's stock market efficient? *Applied Economics Letters*, *11*(11), 707-710. https://doi.org/10.1080/1350485042000236566

Peters, E.E., (1994). Fractal market analysis: *Applying Chaos Theory to Investment & Economics*. John Wiley & Sons, Inc.

Phillips, P.C.B. & Perron P. (1988). Testing for a unit root in time series regression, *Biometrika*, (75), 335-346. https://doi.org/10.2307/2336182

Realized Volatility (2020). *Oxford-Man Institute's quantitative finance realized library, Version: 0.3*. https://realized.oxford-man.ox.ac.uk/data.

Rubinstein, M. (1975). Securities market efficiency in an arrow-debreu economy. *American Economic Review*, *65*(5), 812-824.

Samuelson, P. (1965). Proof that properly anticipated prices fluctuate. *Industrial Management Review*, *6*(2), 41-49.

Saunders, A., Cornett, M.M. (2015). *Financial markets & institutions*. 6th Edition, McGraw-Hill Education.

Tao, Q., Wei, Y., Liu, J. & Zhang, T. (2018). Modeling & forecasting multifractal volatility established upon the heterogeneous market hypothesis. *International Review of Economics & Finance*, (54), 153-153.

Taylor, S.J. (1994). Modeling stochastic volatility: a review & comparative study. *Math. Finance*, (4), 183–204. https://doi.org/10.1111/j.1467-9965.1994.tb00057.x

Volatility Index (2020). *Federal Reserve Bank of St. Louis; Chicago Board Options Exchange Volatility Index*. https://alfred.stlouisfed.org

Wei, Y., & Wang, P. (2008). Forecasting volatility of SSEC in Chinese stock market using multifractal analysis. *Physica A Statistical Mechanics & Its Applications*, *387*(7), 1585–1592. https://doi.org/10.1016/j.physa.2007.11.015

Worthington, A.C. & Higgs, H. (2004). Random walks & market efficiency in European equity markets. *Global Journal of Finance & Economics*, *1*(1), 59-78.

Zivot, E.& Andrews, K. (1992). Further evidence on the great crash, the oil price shock, and the unit root hypothesis. *Journal of Business and Economic Statistics*, *10*(3), 251–270. https://doi.org/10.2307/1391541

Zuckerman, E.W. (2012). Market efficiency: A sociological perspective. *Handbook of the sociology of finance*. Alex Preda & Karin Knorr-Cetina(Eds.), Oxford University Press.