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Research article

Asymmetry Effects in Volatility on the Major European Stock Markets: the EGARCH Based Approach

Joanna Olbrys[1,*] and Elzbieta Majewska[2]

[1] Faculty of Computer Science, Bialystok University of Technology, Wiejska 45A, 15-351 Bialystok, Poland
[2] Faculty of Mathematics and Informatics, University of Bialystok, K. Ciolkowskiego 1M, 15-245 Bialystok, Poland

* **Correspondence:** Email: j.olbrys@pb.edu.pl; Tel: +48-85-746-9050.

Abstract: The main goal of this paper is to investigate the asymmetric impact of innovations on volatility in the case of the largest European stock markets in the United Kingdom, France and Germany by using the EGARCH based approach. The sample period begins in January 2003 and ends in December 2016, and it includes the 2007 U.S. subprime crisis. The robustness analysis of empirical results is provided with respect to the whole sample and three adjacent subsamples, each of equal size: 1) the pre-crisis, 2) the Global Financial Crisis (GFC) and 3) the post-crisis periods. The GFC periods are formally detected by using a statistical method of dividing market states into bullish and bearish markets. Moreover, the common trading window procedure is employed to avoid the nonsynchronous trading problem in the group of investigated markets and to get the overlapping information set. We estimate univariate EGARCH models based on daily percentage logarithmic returns of major stock market indexes: FTSE100 (London), CAC40 (Paris), and DAX (Frankfurt). Pronounced negative asymmetry effects in volatility are presented in the case of all markets and are rather robust to the choice of the period. Our findings are consistent with the literature and suggest that the major European stock markets are more sensitive to 'bad' than 'good' news.

Keywords: volatility; asymmetry effect; Global Financial Crisis; overlapping information set; univariate EGARCH model

1. Introduction

Undoubtedly, there are extremely more 'bad' than 'good' news during the bear market periods. Nelson (1991) points out that researchers beginning with Black (1976) have found the evidence that stock returns are negatively correlated with changes in returns volatility, i.e. volatility tends to rise in response to 'bad news' (excess returns lower than expected) and to fall in response to 'good news' (excess returns higher than expected).

The purpose of this paper is to investigate the asymmetric impact of innovations on volatility in the case of three largest European stock markets in the UK, France and Germany, using univariate EGARCH approach (Nelson, 1991). We try to deal with the 'nonsynchronous trading effect II' (Olbrys, 2013a) by using a 'common trading window' procedure and estimating suitable EGARCH models based on daily percentage logarithmic returns for the major European stock market indexes: FTSE100 (London), CAC40 (Paris) and DAX (Frankfurt). The main goal is to obtain an overlapping information set in the case of all markets, as we plan to test the impact of common 'bad' and 'good' news. We compare empirical results for the whole sample period from January 2, 2003 to December 30, 2016 and three adjacent subsamples, each of equal size: 1) the pre-crisis, 2) the Global Financial Crisis (GFC) and 3) the post-crisis periods. The impact of 'bad' and 'good' news is described in terms of univariate EGARCH models. We observe pronounced negative asymmetry effects in the case of all investigated markets and the results turn out to be robust to the choice of the period.

The remainder of the study is organized as follows. Section 2 specifies a methodological background and a brief literature review. First, we stress the validity of nonsynchronous trading problems. Next, we use a formal statistical procedure of dividing market states into bullish and bearish markets to detect 'down market' (crisis) periods in the analyzed countries. A brief theoretical framework concerning EGARCH (p, q) models is also presented. In Section 3, we describe the data and discuss empirical results of the asymmetric impact of innovations on volatility in the group of investigated markets. Conclusion recalls the main findings and sums them up.

2. Methodological Background

2.1. The nonsynchronous trading problem

According to the literature, one can distinguish between two nonsynchronous trading effect problems (Olbrys, 2013a). The first problem, called 'nonsynchronous trading effect I', occurs when we analyze one selected domestic stock market. Stock tradings do not occur in a synchronous manner. Different stocks have different trading frequencies and even for a single stock the trading intensity varies from hour to hour and from day to day. The actual time of last transaction of the stock varies from day to day. As such we incorrectly assume daily returns as an equally spaced time series with a 24-hour interval (Tsay, 2010). The non-trading effect induces potentially serious biases in the moments and co-moments of asset returns such as their means, variances, covariances, betas, autocorrelation and cross-autocorrelation coefficients (Campbell et al., 1997). The second and potentially serious problem, called 'nonsynchronous trading effect II', occurs when we examine the relations between stock markets in various countries. The national stock markets are operating in diverse time zones with different opening and closing times, thereby making return observations nonsynchronous (Eun and Shim, 1989; Olbrys, 2013a). These differences arise naturally from the fact

that trading days in different countries are subject to different national and religious holidays, unexpected events and so forth (Baumöhl and Výrost, 2010).

In this paper, we investigate the asymmetric impact of innovations on volatility in the case of three largest European stock markets in the UK, France and Germany. Therefore, we have to deal with the 'nonsynchronous trading effect II'. Many studies attempted various methods to deal with this problem. Some researchers use weekly or monthly data to avoid the non-trading effect. Such solutions, however, may lead to small sample sizes and cannot capture the information transmission in shorter (daily) timeframes (Baumöhl and Výrost, 2010). Other papers present various daily data-matching procedures. We employ the following approach, also called a 'common trading window': the data are collected for the same dates across the stock markets, removing the data for those dates when any series has a missing value due to no trading (Eun and Shim, 1989; Booth et al., 1997; Olbrys, 2013a; Olbrys and Majewska, 2014b). It is important to note that the use of a wide range of time-series models could be questionable if non-synchronicities are not accounted for, especially because the current implementations of these models in most econometric software inherently assume synchronous data.

2.2. Direct identification of crisis periods on the major European stock markets

Direct quantitative identification of crisis periods is possible based on statistical procedures of dividing market states into bullish and bearish markets. Fabozzi and Francis (1977) stress that no just one definition of bull and bear markets exists. Therefore, they proposed three alternative definitions of bull and bear market conditions. The first categorization was based on market trends. The second partitioning procedure ignored market trends and viewed the market portfolio return every month independently. The third procedure partitioned the sample into three subsets: (1) months when the market moved up substantially, (2) months when the market moved down substantially and (3) months when the market moved neither up nor down substantially. Substantial moves were arbitrarily defined as months when the absolute value of market return was larger than half of one standard deviation of the market returns measured over the total sampled period (Fabozzi and Francis, 1977).

Pagan and Sossounov (2003) developed an algorithm that seemed to be successful in locating periods in time that were considered bull and bear markets in U.S. equity prices. They tested monthly data of the New York market index-S&P500, in the period from January 1835 to May 1997. Lee et al. (2011) use a modified version of the Pagan and Sossounov (2003) method of dividing market states into bullish and bearish markets. They analyze the Taiwanese market, in the period from January 1997 to December 2007. Lee et al. (2011) point out that investors usually cannot identify the present market state and they often refer to past market states as they make investment decisions.

We employ a three-stage procedure of dividing market states into up and down markets. Our methodology builds on Pagan and Sossounov (2003). In the first step, we conduct a preliminary identification of turning points, i.e., peaks and troughs, based on the conditions (1)–(2), respectively:

$$\ln P_{t-8},\ldots,\ln P_{t-1} < \ln P_t > \ln P_{t+1},\ldots,\ln P_{t+8} \tag{1}$$

$$\ln P_{t-8},\ldots,\ln P_{t-1} > \ln P_t < \ln P_{t+1},\ldots,\ln P_{t+8} \tag{2}$$

where P_t represents the market index of month t, and from successive peaks/troughs we choose the highest/deepest one, respectively. Pagan and Sossounov (2003) stress that in the business cycle

literature an algorithm for describing turning points in time series was developed by Bry and Boschan (1971), but they modified this algorithm by taking the eight months window (instead of six) in marking the initial location of turning points. The main goal was not to smooth any of the monthly, already smoothed, data. In the second step, we rule out the phases (peak-trough or trough-peak) that last for less than four months and cycles (peak-trough-peak or trough-peak-trough) that last for less than sixteen months. Pagan and Sossounov (2003) point out that in business cycle dating the minimal cycle length is fifteen months, hence sixteen months were chosen to create a symmetric window of eight periods. Moreover, they advocated four months as the minimal length of a phase.

In the last step we calculate the amplitudes A for each phase (amplitude is the difference in the natural logs of the index value in subsequent turning points). During the bull/bear market period there must be a large enough (of at least 20%) rise/fall in the index value (Pagan and Sossounov, 2003). This means that the amplitude of a given phase must fulfill the condition $A \geq 0.18$ or $A \leq -0.22$ for the bull or bear market period, respectively. Indeed, if a growth of the index value in an up market period will equal at least to 20%, then (Olbrys and Majewska, 2014a):

$$A = \ln P_{t+1} - \ln P_t = \ln \frac{P_{t+1}}{P_t} > \ln \frac{1.2 \cdot P_t}{P_t} = \ln 1.2 \approx 0.18 \tag{3}$$

By analogy, if a decline of the index value in a down market period will equal at least to 20%, then:

$$A = \ln P_{t+1} - \ln P_t = \ln \frac{P_{t+1}}{P_t} < \ln \frac{0.8 \cdot P_t}{P_t} = \ln 0.8 \approx -0.22 \tag{4}$$

The data consists of monthly logarithmic returns of three major developed European stock market indexes: FTSE100, CAC40 and DAX. Figures 1–3 present down market periods for the market indexes obtained from the procedure described above, in the whole sample from January 2003 to December 2016. The horizontal axis stands for time (months), and the vertical axis stands for the market index. Vertical lines and light grey areas stand for down market periods.

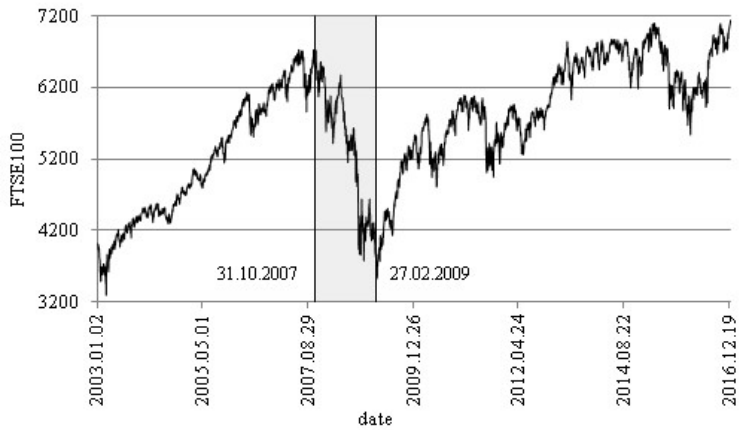

Figure 1. October 31, 2007—February 27, 2009 as the GFC period for FTSE100 (London).

Source: Authors' calculations.

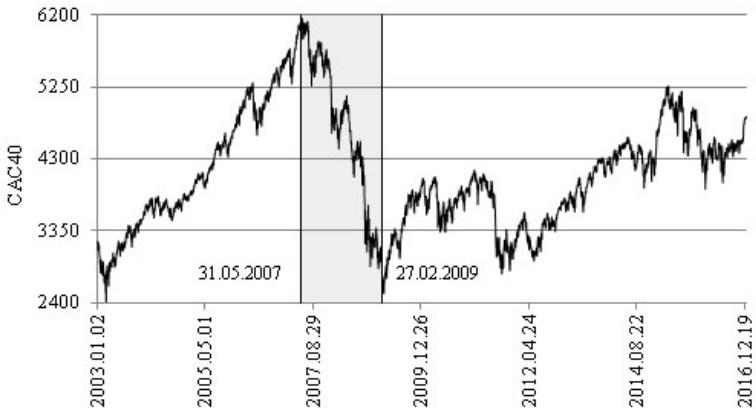

Figure 2. May 31, 2007—February 27, 2009 as the GFC period for CAC40 (Paris).

Source: Authors' calculations.

Figure 3. December 28, 2007—February 27, 2009 as the GFC period for DAX (Frankfurt).

Source: Authors' calculations.

The obtained results reveal that October 2007—February 2009 was the Global Financial Crisis (GFC) period for the stock market in London. The GFC period for the Paris stock exchange was longer and it lasted from May 2007 to February 2009, while the crisis period for the Frankfurt stock market was shorter and it lasted from December 2007 to February 2009. Our results confirm February 2009 as the end of down markets in all investigated countries (Olbrys and Majewska, 2014a). The precise identification of market states is certainly important in practice, as many researchers found that profits to investment strategies depend critically on the state of the market. Moreover, it is instructive to formally identify crises, as it enables the examination of various relationships among international stock markets, taking into consideration the pre-, post- and crisis periods (Olbryś and Majewska, 2015).

2.3. The exponential GARCH model

Many researchers documented that stock return volatility tends to rise following 'good' and 'bad' news. This phenomenon was noted both for individual stocks and for market indexes (Braun et al., 1995). Since Nelson (1991) introduced the univariate Exponential Generalized Autoregressive Conditionally Heteroskedastic (EGARCH) model, some researchers employ this model to capture the asymmetric effect of innovations on volatility. Engle and Ng (1993) stress that the main advantage of EGARCH model is that it allows 'good' news and 'bad' news to have a different impact on volatility, while the standard GARCH model does not.

Several studies present various applications of univariate and multivariate EGARCH models. Koutmos and Booth (1995) investigate the transmission mechanism of price and volatility spillovers across the New York, Tokyo and London stock markets from three different time zones, using the EGARCH approach. Jane and Ding (2009) propose the multivariate extension of Nelson's univariate EGARCH model and compare their model with the existing one given by Koutmos and Booth (1995). Booth et al. (1997) provide the evidence on price and volatility spillovers among four Scandinavian (Nordic) stock markets. Bhar (2001) applies an extended bivariate EGARCH model to provide evidence of linkages between the equity market and the index futures market in Australia. Reyes (2001) examines volatility transfers between size–based indexes from the Tokyo Stock Exchange, using a bivariate EGARCH model. Tse et al. (2003) employ a bivariate EGARCH model that allows for both mean and variance spillovers between the US and Polish stock markets. Yang and Doong (2004) adopt a bivariate EGARCH framework to investigate price and volatility spillovers between stock prices and exchange rates in the group of the G-7 countries. Balaban and Bayar (2005) test the relationship between stock market returns and their forecast volatility derived from the symmetric and asymmetric GARCH-type models in 14 countries. Bhar and Nikolova (2009) investigate the level of integration and the dynamic relationship between the BRIC countries (i.e. Brazil, Russia, India and China) using bivariate EGARCH framework. Curto et al. (2009) employ the MSV-EGARCH specification to explore links between stock market returns, volatility and treading volume in the case of six major international stock market indexes. Lee and Stewart (2010) examine asymmetric effects on volatility in the case of the Baltic and Nordic major stock indexes, using both univariate and multivariate EGARCH models. Olbrys (2013a) investigates the interdependence of price volatility across the US developed stock market and two emerging Central and Eastern European (CEE) markets in Warsaw and Budapest using a multivariate modified EGARCH model. Abbas et al. (2013) analyze volatility transmission from one market to another in the case of selected Asian stock markets in Pakistan, China, Sri Lanka and India, as well as developed equity markets in the US, UK, Japan and Singapore. The authors employ bivariate EGARCH model and results show that volatility transmission is present especially between friendly countries in different regions with economic links. Kuttu (2014) uses MVAR-EGARCH model to examine the return and volatility dynamics between thin-traded adjusted equity returns from Ghana, Kenya, Nigeria, and South Africa. Dedi and Yavas (2016) explore linkages between equity market returns and volatility spillovers in the UK, Germany, China, Russia, and Turkey. They apply EGARCH model among various GARCH methodologies.

The asymmetric effects of innovations on volatility for one selected domestic stock market could be well described by the univariate EGARCH model (Olbryś, 2013b) although it is now widely accepted that a multivariate modeling framework (in the case of the group of markets) leads to more relevant empirical models than working with separate univariate models (Bauwens et al., 2006). But it

is worth stressing that a multivariate EGARCH model estimation is particularly difficult due to the large number of estimated parameters, especially when we use a sample of a relatively small size.

The univariate time series $\{R_t\}$ can be expressed as:

$$R_t = \mu_t + \varepsilon_t, \tag{5}$$

where: $\mu_t = E(R_t | F_{t-1})$ is the conditional expectation of R_t given the past information F_{t-1}, ε_t is the innovation of the series at time *t*.

Nelson's univariate EGARCH (p, q) model can be represented as follows (Tsay, 2010):

$$\begin{aligned} &\ln(\sigma_t^2) = \alpha_0 + \frac{1+\beta_1 B + \cdots + \beta_{q-1} B^{q-1}}{1-\alpha_1 B - \cdots - \alpha_p B^p} \cdot g(z_{t-1}), \\ &\varepsilon_t = \sigma_t \cdot z_t, \\ &\varepsilon_t | F_{t-1} \sim N(0, \sigma_t), z_t \sim N(0,1) \end{aligned} \tag{6}$$

$$g(z_t) = \theta \cdot z_t + \gamma \cdot [|z_t| - E(|z_t|)], \tag{7}$$

where: $\sigma_t = Var(R_t | F_{t-1})$ is the conditional variance of R_t given the past information F_{t-1}, α_0 is a constant, *B* is the back-shift (or lag) operator such that $Bg(z_t) = g(z_{t-1})$, $1 + \beta_1 B + \cdots + \beta_{q-1} B^{q-1}$ and $1 - \alpha_1 B - \cdots - \alpha_p B^p$ are polynomials with zeros outside the unit circle and have no common factors.

The value of $g(z_t)$ depends on several elements. Nelson (1991) points out that to accommodate the asymmetric relation between stock returns and volatility changes, the value of $g(z_t)$ must be a function of both the magnitude and the sign of z_t. In Eq. (7), $g(z_t)$ is a linear combination of z_t and $[|z_t| - E(|z_t|)]$ with coefficients θ and γ. The term in the bracket measures the magnitude effects and the coefficient γ relates lagged standardized innovations to volatility in a symmetric way. The term $\theta \cdot z_t$ measures the sign effects and the coefficient θ relates standardized shocks to volatility in an asymmetric style. $\{g(z_t)\}_{t=-\infty,\infty}$ is an i.i.d. random sequence with mean zero (Jane and Ding 2009). For $\theta < 0$ the future conditional variances will increase proportionally more as a result of a negative shock than for a positive shock of the same absolute magnitude (Bollerslev and Mikkelsen 1996). Both z_t and $[|z_t| - E(|z_t|)]$ are zero mean i.i.d. random sequences with continuous distributions. The asymmetry of $g(z_t)$ can be easily seen by rewriting it as:

$$g(z_t) = \begin{cases} (\theta + \gamma) \cdot z_t - \gamma \cdot E(|z_t|) \ if \ z_t \geq 0, \\ (\theta - \gamma) \cdot z_t - \gamma \cdot E(|z_t|) \ if \ z_t < 0. \end{cases} \tag{8}$$

Since EGARCH (p, q) = EGARCH(1, 1) is a simple case, Eq. (6) becomes:

$$(1 - \alpha_1 B) \cdot \ln(\sigma_t^2) = (1 - \alpha_1 B) \cdot \alpha_0 + g(z_{t-1}), \tag{9}$$

Eq. (9) can be rewritten (subscript of α_1 is omitted) and then:

$$\ln(\sigma_t^2) = \alpha_0^* + \alpha \cdot \ln(\sigma_{t-1}^2) + g(z_{t-1}), \tag{10}$$

where $\alpha_0^* = const$.

The parameter α in Eq. (10) determines the influence of the past conditional volatility on the current conditional volatility. For the conditional volatility process to be stationary, $|\alpha| < 1$ is

required. The persistence of volatility may be also quantified by examination of the half–life (*HL*) defined by:

$$HL = \frac{\ln(0.5)}{\ln|\alpha|} \tag{11}$$

which measures the time period required for the innovations to be reduced to one–half of their original size.

Let $R_{i,t}$ be the percentage logarithmic return at time *t* for market *i* (i=1, 2, 3, where 1=London, 2=Paris, and 3=Frankfurt). Then, the univariate AR (1)–EGARCH (1, 1) model for market *i* may be written as follows:

$$\begin{aligned} R_{i,t} &= \varphi_{i,0} + \varphi_i R_{i,t-1} + \varepsilon_{i,t}, \\ \ln(\sigma_{i.t}^2) &= \alpha_{i.0}^* + \alpha_i \cdot \ln(\sigma_{i.t-1}^2) + \theta_i \cdot z_t + \gamma_i \cdot [|z_t| - E(|z_t|)]. \end{aligned} \tag{12}$$

3. Empirical Results

3.1. Data description and preliminary statistics

The data consists of daily percentage logarithmic returns for major stock market indexes for London (FTSE100 index), Paris (CAC40 index), and Frankfurt (DAX index). As mentioned in Introduction, the goal was to obtain the overlapping information set in the case of all markets, as we planned to test the impact of common 'bad' and 'good' news. We used the 'common trading window' procedure and removed the data for those dates when any series has a missing value due to no trading (Olbrys and Majewska, 2014b). Thus all the data are collected for the same dates across three markets and finally there are 3509 observations for each series for the period beginning January 2, 2003 and ending December 30, 2016. It is worth stressing that the reduction in the number of observations is not substantial, as the group of markets is small (Olbrys and Majewska, 2014b). Table 1 reports summarized statistics for daily percentage logarithmic returns for three stock indexes (in order of decreasing value of market capitalization at the end of 2015), as well as statistics testing for normality and interdependence.

Several results in Table 1 are worth special notice. The sample means are not statistically different from zero. The measure for skewness shows that the FTSE100 return series is negatively and significantly skewed, while the measure for excess kurtosis shows that all return series and highly leptokurtic with respect to the normal distribution. The Doornik-Hansen (2008) test rejects normality for each of the return series at the 5 per cent level of significance. The Ljung-Box (1978) statistic at the lag $q \approx lnT$, where *T* is the number of data points (Tsay, 2010), calculated for both the return and the squared return series, indicates the presence of significant linear and non-linear dependencies, respectively. The linear dependences may be due to the 'nonsynchronous trading effect I' of the stocks that make up each index (Campbell et al., 1997). The non–linear dependences may be due to the autoregressive conditional heteroskedasticity (Nelson, 1991; Koutmos and Booth, 1995; Booth et al., 1997). Calculations have been conducted using the open-source computer software Gretl 1.10.1 (Adkins, 2014).

Table 1. Summarized statistics for daily percentage logarithmic returns for three stock indexes: FTSE100 (London), CAC40 (Paris), and DAX (Frankfurt).

	Index	Market Cap. EUR Billion, Dec 2015	Mean	St. Dev.	Skewness	Excess kurtosis	Doornik-Hansen test	LB(8)	$LB^2(8)$
1	FTSE100	3009.5	0.017	1.169	-0.119 [0.004]	7.722 [0.000]	2547.86 [0.000]	46.81	2020.92
2	CAC40	1911.2	0.014	1.432	-0.009 [0.822]	5.909 [0.000]	1803.01 [0.000]	37.20	1234.00
3	DAX	1781.6	0.039	1.428	-0.015 [0.714]	5.239 [0.000]	1529.57 [0.000]	18.54	1102.94

Source: Authors' calculations and http://sdw.ecb.europa.eu.

Notes: The table is based on all sample observations during the period January 2, 2003–December 30, 2016. The test statistic for skewness and excess kurtosis is the conventional *t*-statistic. The Doornik-Hansen test (2008) has a χ^2 distribution if the null hypothesis of normality is true. Numbers in brackets are *p*-values. LB (q) and LB^2 (q) are the Ljung-Box (1978) statistics for returns and squared returns, respectively, distributed as $\chi^2(q)$, $q \approx lnT$, where T is the number of data points (Tsay, 2010). The χ^2 (8) critical value is equal to 15.51 (5%).

3.2. Asymmetric impact of innovations on volatility on the major European stock markets

To examine asymmetric effects between positive and negative index return innovations, we first estimate the univariate AR (1)–EGARCH (1, 1) models of three stock indexes: FTSE100 (London), CAC40 (Paris) and DAX (Frankfurt), in the whole sample period from January 2, 2003 to December 30, 2016. The robust QML (Bollerslev and Wooldridge, 1992) estimates of the parameters of the model (12) are presented in Table 2.

In the case of all analyzed periods, the choice of an appropriate version of the EGARCH model was conducted based on the BIC and AIC information criterions, and distributions for the innovations were supposed to be normal, t-Student, or skewed t. As it turned out, the univariate AR (1)–EGARCH (1, 1) models with skewed t as the distribution for the innovations are the most adequate for all series in the whole sample period. Calculations concerning EGARCH models have been done using GAUSS package with FANPAC MT 3.0 module.

For model checking, the Ljung-Box statistics LB (20) for the standardized innovation process and LB^2 (20) for the squared standardized innovations have been applied (Baillie and Bollerslev, 1990). The evidence is that there is no serial correlation or conditional heteroskedasticity in the standardized innovations of the fitted models in the whole sample period. Therefore we can conclude that the estimated AR (1)–EGARCH (1, 1) models are adequate (Tsay, 2010).

Table 2. Results from the AR (1)–EGARCH (1, 1) models of three stock indexes: FTSE100, CAC40, and DAX, in the whole sample period from January 2, 2003 to December 30, 2016 (3509 daily observations).

	London (i=1)	Paris (i=2)	Frankfurt (i=3)
The distribution for the innovations (the best fitted model)	skewed t	skewed t	skewed t
	Conditional mean equation		
$\varphi_{i,0}$	0.006 (0.013)	0.007 (0.017)	0.035 (0.019)
φ_i	-0.040* (0.017)	-0.051* (0.016)	-0.014 (0.025)
	Conditional variance equation		
$\alpha^*_{i,0}$	-0.103* (0.015)	-0.072* (0.010)	-0.089* (0.010)
α_i	0.981* (0.004)	0.977* (0.005)	0.979* (0.004)
θ_i	-0.142* (0.014)	-0.163* (0.017)	-0.135* (0.016)
γ_i	0.129* (0.018)	0.102* (0.014)	0.125* (0.014)
	Conditional density parameters		
ν_i	13.568* (2.735)	10.380* (1.715)	9.219* (1.428)
λ_i	-0.151* (0.023)	-0.138* (0.024)	-0.133* (0.021)
	Asymmetry effect for market i		
$\delta_i = \theta_i / \gamma_i$	-1.10 < 0	-1.60 < 0	-1.08 < 0
Half–life (*HL*)	36.13	29.79	32.66
Log–likelihood	-4659.73	-5503.42	-5544.81
LB(20)	11.55 [0.93]	23.12 [0.28]	20.58 [0.42]
$LB^2(20)$	26.13 [0.16]	7.84 [0.99]	15.35 [0.76]

Source: Authors' calculations

Notes: * denotes significance at the 5 per cent level. The heteroskedastic consistent standard errors are in parentheses. The variance-covariance matrix of the estimated parameters is based on the QML algorithm. The distribution for the innovations is supposed to be skewed t; ν and λ are conditional density parameters (Lucchetti and Balietti, 2011). The asymmetry coefficient is defined in the text. The half-life is defined in the text and represents the time it takes for the shock to reduce its impact by one-half. LB (20) and LB^2 (20) denotes the Ljung-Box (1978) statistics for standardized innovations and squared standardized innovations, respectively (Baillie and Bollerslev, 1990). Numbers in brackets are *p*-values.

Several results presented in Table 2 are worth a comment. The autoregressive coefficients φ_i are negative and statistically significant for the London and Paris markets. The conditional variance is a function of past conditional variances and past innovations. The relevant coefficients α_i, θ_i and γ_i are statistically significant at the 5 per cent level in the case of all models. In addition, all of the γ_i coefficients are positive. For positive γ_i, if $\delta_i = \theta_i / \gamma_i < 0$, then negative innovations have a higher impact on volatility than positive innovations. If $\delta_i = 0$ ($\theta_i = 0$ and $\gamma_i > 0$), then the magnitude terms raises (lowers) volatility when the magnitude of market movements is large (small). If $0 < \delta_i < 1$, then positive innovations would increase volatility but negative innovations decrease volatility. These pronounced negative asymmetry effects are present in Table 2. For London, Paris, and Frankfurt, negative innovations increase volatility considerably more than positive innovations. Our findings suggest that the investigated stock markets are more sensitive to 'bad' than 'good' news.

The persistence of volatility may be interpreted by using the half-life concept (11), which measures the time it takes for an innovation to reduce its impact by one half. Numerically, the *HL* coefficients for the London, Paris, and Frankfurt indexes are equal to: 36.13, 29.79 and 32.66 days, respectively. It is worth stressing that the half–life coefficients are rather high, however Olbryś (2013b) documents that half–life coefficients for the New York, Warsaw, Prague, and Budapest indexes are equal to: 31.16, 40.43, 29.79, and 32.66 days, respectively. Moreover, Scheicher (2001) documents half–life coefficients for the CTX, HTX, and PTX indexes, which are equal to: 16.39, 1.95, and ∞ (!) days. Bhar (2001) reports half–life coefficients equal to 2.63 and 3.86 days for two Australian spot and futures markets.

Subsequent Tables 3–5 present details concerning further numerical results from the AR(1)–EGARCH(1, 1) models of three stock indexes in three adjacent subsamples, each of equal size: (1) the pre-GFC (Table 3), (2) the GFC (Table 4) and (3) the post-GFC (Table 5) periods, respectively. As mentioned in subsection 2.2, we have obtained different GFC periods for analyzed stock markets (see Figures 1–3), hence the corresponding adjacent subperiods are different as well.

The results in Tables 3–5 reveal that the asymmetric effects between positive and negative index return innovations are presented for all markets and turn out to be robust to the choice of the period. Almost all of the γ_i coefficients are significantly positive and almost all of the θ_i coefficients are significantly negative (at the 5 percent level). Hence, the corresponding $\delta_i = \theta_i / \gamma i$ coefficients are negative, except for the DAX index during the post-GFC period, which is reported in Table 5. However, the DAX best fitted EGARCH model is qualitatively rather poor. Therefore, we can conclude that negative innovations have a higher impact on the volatility than positive innovations. This evidence confirms that the investigated European stock markets are more sensitive to 'bad' than 'good' news, regardless of the subperiod choice. The half-life coefficients (11), which measure the persistence of volatility for the London, Paris, and Frankfurt indexes during the pre-, crisis and post-crisis periods are equal to: (1) 16.98, 12.98 and 8.54 days (for the pre-GFC period – Table 3), (2) 22.76, 23.55 and 24.40 days (for the GFC period–Table 4) and (3) 16.15, 10.48 and 692.80 days (for the post-GFC period–Table 5), respectively. However, as mentioned, the quality of the best fitted EGARCH model for the Frankfurt Stock Exchange is rather low (for details see Table 5). Excluding the DAX index, the results for FTSE100 and CAC40 indexes during the pre- and post-GFC periods are quantitatively almost the same, while during the GFC period the *HL* values, which inform about time required for innovations to be reduced to one–half of their original size, are slightly higher for all stock markets.

Table 3. Results from the AR (1)–EGARCH (1, 1) models of three stock indexes: FTSE100, CAC40, and DAX, in the pre-GFC period.

	London (i=1)	Paris (i=2)	Frankfurt (i=3)
Pre-GFC period	11.07.2006–30.10.2007 331 daily observations	1.09.2005–30.05.2007 439 daily observations	30.10.2006–27.12.2007 292 daily observations
The distribution for the innovations (the best fitted model)	normal	t-Student	skewed t
	Conditional mean equation		
$\varphi_{i,0}$	0.003 (0.042)	0.070 (0.039)	0.074 (0.053)
φ_i	0.020 (0.054)	-0.121* (0.048)	-0.043 (0.064)
	Conditional variance equation		
$\alpha^*_{i,0}$	-0.116 (0.060)	-0.032 (0.039)	-0.094* (0.047)
α_i	0.960* (0.021)	0.948* (0.020)	0.922* (0.051)
θ_i	-0.171* (0.042)	-0.196* (0.037)	-0.158* (0.064)
γ_i	0.127 (0.069)	0.013 (0.045)	0.111 (0.058)
	Conditional density parameters		
ν_i	–	16.189 (13.063)	8.957 (5.524)
λ_i	–	–	-0.206* (0.087)
	Asymmetry effect for market i		
$\delta_i = \theta_i / \gamma_i$	-1.35 < 0	-15.08 < 0	-1.42 < 0
Half–life (*HL*)	16.98	12.98	8.54
Log–likelihood	-391.26	-527.81	-382.62
LB(20)	16.96 [0.66]	17.98 [0.59]	14.19 [0.82]
$LB^2(20)$	8.01 [0.99]	14.78 [0.79]	13.95 [0.83]

Source: Authors' calculations.

Notes: See Table 2 for explanations.

Table 4. Results from the AR (1)–EGARCH (1, 1) models of three stock indexes: FTSE100, CAC40 and DAX, in the GFC period.

	London (i=1)	Paris (i=2)	Frankfurt (i=3)
GFC period	31.10.2007–27.02.2009 331 daily observations	31.05.2007–27.02.2009 439 daily observations	28.12.2007–27.02.2009 292 daily observations
The distribution for the innovations (the best fitted model)	normal	normal	skewed t
	Conditional mean equation		
$\varphi_{i,0}$	-0.233* (0.094)	-0.199* (0.000)	-0.224* (0.000)
φ_i	-0.119* (0.052)	-0.087* (0.000)	-0.030* (0.000)
	Conditional variance equation		
$\alpha^*_{i,0}$	-0.059 (0.034)	-0.086* (0.033)	-0.030 (0.037)
α_i	0.970* (0.013)	0.971* (0.010)	0.972* (0.010)
θ_i	-0.136* (0.032)	-0.193* (0.040)	-0.177* (0.033)
γ_i	0.128* (0.045)	0.151* (0.038)	0.085* (0.041)
	Conditional density parameters		
ν_i	–	–	11.092 (7.300)
λ_i	–	–	-0.061 (0.077)
	Asymmetry effect for market i		
$\delta_i = \theta_i / \gamma_i$	-1.06 < 0	-1.28 < 0	-2.08 < 0
Half–life (*HL*)	22.76	23.55	24.40
Log–likelihood	-667.62	-853.18	-599.32
LB(20)	17.01 [0.65]	17.00 [0.65]	8.91 [0.98]
$LB^2(20)$	21.33 [0.38]	33.59 [0.03]	35.59 [0.02]

Source: Authors' calculations.

Notes: See Table 2 for explanations.

Table 5. Results from the AR (1)–EGARCH (1, 1) models of three stock indexes: FTSE100, CAC40, and DAX, in the post-GFC period.

	London (i=1)	Paris (i=2)	Frankfurt (i=3)
Post-GFC period	2.03.2009–28.06.2010 331 daily observations	2.03.2007–26.11.2010 439 daily observations	2.03.2009–30.04.2010 292 daily observations
The distribution for the innovations (the best fitted model)	normal	normal	normal
	Conditional mean equation		
$\varphi_{i,0}$	0.070 (0.061)	0.030 (0.060)	0.152 (0.089)
φ_i	-0.020 (0.062)	-0.060 (0.049)	-0.060 (0.071)
	Conditional variance equation		
$\alpha^*_{i,0}$	-0.135* (0.034)	-0.093* (0.038)	-0.027 (0.076)
α_i	0.958* (0.022)	0.936* (0.028)	0.999* (0.006)
θ_i	-0.144* (0.056)	-0.185* (0.059)	0.019 (0.045)
γ_i	0.190* (0.044)	0.182* (0.044)	0.030 (0.099)
	Asymmetry effect for market i		
$\delta_i = \theta_i / \gamma_i$	-0.76 < 0	-1.02 < 0	0.63 > 0
Half–life (*HL*)	16.15	10.48	692.80
Log–likelihood	-531.96	-779.07	-523.18
LB(20)	22.06 [0.34]	15.53 [0.75]	14.41 [0.81]
$LB^2(20)$	30.57 [0.06]	40.06 [0.005]	30.64 [0.06]

Source: Authors' calculations.
Notes: See Table 2 for explanations.

4. Conclusion

The aim of this study was to explore the asymmetric impact of innovations on volatility on the major developed European stock markets in the UK, France and Germany, by using the EGARCH based approach. The sample covered the period from January 2003 to December 2016, and it included the 2007 U.S. subprime crisis. The robustness analysis of empirical results was provided with respect to the whole sample and three adjacent subsamples, each of equal size: 1) the pre-GFC, 2) the GFC, and 3) the post-GFC periods. Our research confirmed the pronounced asymmetric impact of innovations on volatility in the case of all analyzed stock markets. We conclude that negative innovations have a higher impact on volatility than positive innovations. Our findings are rather

consistent with the literature and suggest that the investigated stock markets are more sensitive to 'bad' than 'good' news, regardless of the subsample choice. From an investor's point of view it is important that these findings are also in accordance with the investor's intuition. Moreover, the results are essentially not surprising if we take into account that the major European financial markets are strongly connected 'every day', not only during financial crises. Due to the importance of the problem, a possible direction for further research would be an investigation of asymmetry effects in the case of the European stock markets in terms of other asymmetric GARCH-type models (Engle, 2000; Bauwens et al., 2006).

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Conflict of Interest

All authors declare no conflict of interest.

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