

Article

How Does the Financial Crisis Affect Volatility Behavior and Transmission Among European Stock Markets?

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Abstract: The spread of the global financial crisis of 2008/2009 was rapid, and impacted the functioning and the performance of financial markets. Due to the importance of this phenomenon, this study aims to explain the impact of the crisis on stock market behavior and interdependence through the study of the intraday volatility transmission. This paper investigates the patterns of linkage dynamics among three European stock markets—France, Germany, and the UK—during the global financial crisis, by analyzing the intraday dynamics of linkages among these markets during both calm and turmoil phases. We apply a VAR-EGARCH (Vector Autoregressive Exponential General Autoregressive Conditional Heteroscedasticity) framework to high frequency five-minute intraday returns on selected representative stock indices. We find evidence that interrelationship among European markets increased substantially during the period of crisis, pointing to an amplification of spillovers. In addition, during this period, French and UK markets herded around German market, possibly explained by behavior factors influencing the stock markets on or near dates of extreme events. Germany was identified as the hub of financial and economic activity in Europe during the period of study. These findings have important implications for both policymakers and investors by contributing to better understanding the transmission of financial shocks in Europe.

Keywords: stock market behavior; volatility spillover; financial crisis; high frequency data

1. Introduction

The recent global financial crisis has considerably affected financial markets and is considered the most devastating crisis since the Great Depression of 1929. According to data from the World Federation of Exchanges, at the end of 2007 the world equity market capitalization was more than \$64 trillion and sharply declined in 2009 to stand at \$49 trillion—a drop of 22%, which is equal to 25% of global GDP for 2009. This crisis, which mainly originated in the US market, spread rapidly and dangerously to developed and emerging financial markets and to real economy around the world. A study by Bartram and Bodnar [1] provides a broad analysis of the impact of the crisis on global equity markets. Focusing on overall market performance, they show that the world market portfolio total return index continuously declined from mid-September 2008, whereas the 30 day rolling portfolio of world markets, measuring normal volatility of global markets, increased during the same period. The regional market return indices experienced a similar pattern of evolution with, however, a more significant decline in emerging markets, in contrast to developed markets. Comparing the level of correlation of returns between pre-crisis and crisis period, Bartram and Bolnar [1] point out an increase of correlation within a regional market. Considering these results, the study highlights the sudden and relatively unexpected occurrence of this crisis, and raises many questions among academics and practitioners—notably, concerning the nature of stock market linkages and the response of markets to shocks.

This paper contributes to these ongoing debates by investigating the interrelationship between financial markets and their market behavior changes during financial turmoil, especially during periods of high risk. Studying market interrelationship will provide evidence of their market behavior, whereas pointing out sudden changes in cross-market linkages after a shock affecting markets will allow better investigation of the phenomenon of contagion during financial crises. A better understanding of these issues has become the key to portfolio allocation and risk management activities, and therefore central for investors, academics and policymakers.

In our analysis, we adopt the definition of Forbes and Rogobon [2], which stipulates that contagion is “*a significant increase in cross-market linkages*”. Hence, there is contagion between markets if the cross-market linkages increased significantly after a shock. However, if these linkages are continuously at high levels (before and after a shock) there is no contagion, but only interdependence. As noted by Forbes and Rogobon [2], there are a number of different types of cross-market linkages, such as the correlation of asset returns, cross-market correlation coefficients, or the transmission of shocks or volatility.

Since the provocative paper by Forbes and Rogobon [2], there have been an increasing number of approaches trying to assess contagion during financial crises. The most commonly used approach is based on the notion of correlation to study cross-market linkages. Focusing on the 1987 crash, King and Wadhwani [3], and Lee and Kim [4], for instance, find evidence of an increase in stock return correlations. Calvo and Reinhart [5], and Baig and Goldfajn [6] studied Mexican and Asian crises

respectively, and report correlation shifts during the turmoil periods. With the recent global financial crisis, there has been renewed interest by academicians and researchers in analyzing of the transmission of the crisis. By using a factor model to predict returns and correlation as indicative of contagion, Bekaert *et al.* [7] find significant evidence of contagion from US markets and the global financial sector.

Using more advanced techniques, such as a multivariate regime-switching copula model, Kenourgios *et al.* [8] investigate contagion on four emerging and two developed markets during five recent financial crises (the Asian crisis, the Russian crisis, the Technology Bubble Collapse, and the Brazilian and Subprime Crises). Their empirical results confirm the contagion phenomenon.

Syllignakis and Kouretas [9] investigated the returns correlation among mainly Central and Eastern European (CEE) emerging markets and the US, Germany, and Russia during financial crises. Using a dynamic conditional correlations approach, they provide substantial evidence of contagion, mainly due to herding behavior in the financial markets of the CEE markets. However, during the Asian and Russian crises and the technology bubble, the hypothesis of financial contagion was refuted.

A second approach of studying cross-market linkages is based on testing for changes in the cointegrating vector between markets [10], whereas the third approach is to examine international transmission mechanisms and see to what extent different factors can affect the market during financial crises [11,12].

A final approach is to use ARCH-GARCH framework to analyze the transmission of volatility between markets. Dungey and Martin [13], for example, studied spillovers and contagion across different equity and currency markets during the East Asian crisis, mainly by analyzing the transmission of volatility across markets. The empirical results prove that the spillover effects were relatively larger than contagion effects. Considering three emerging market crises (Asian, Russian and Argentine) and the subprime crisis of 2007, Kenourgios and Padhi [14] used two different empirical methodologies (Johansen cointegration tests and vector error correction model, and the Asymmetric Generalized Dynamic Conditional Correlation AG-DCC GARCH model) to investigate financial contagion. The empirical results provide evidence of the contagion of the subprime, Asian and Russian crisis. However, mitigated results concerning the Argentine crisis were observed depending on the methodology used and the markets studied.

Focusing mainly on BRIC's stock markets (Brazil, Russia, India, China), Aloui *et al.* [15] show strong evidence of dependence between markets during the Global Financial Crisis, using copula functions and GARCH-M model. These results are confirmed by the study of Dimitriou *et al.* [16].

A related work on contagion attempts to explain the transmission of volatility among stock markets, generally known as the volatility-spillover literature. Some studies on international spillovers concentrate on developed markets, especially the US, Japanese and major European markets (e.g., [17–19]). The conclusions concerning linkage between European and US markets reveal that of European markets only the UK and German are affected by the US market [18].

Other studies in this strand concentrate on emerging markets. Some focus on analyzing integration and interdependence in volatility across emerging markets, while others study the link between developing and developed markets.

Work related to this literature attempts to explain the transmission of shocks, and concentrates on financial crises and their effects on the evolution of financial spillovers and market behavior. Focusing

on the Asian crisis, Gosh *et al.* [20] classify three types of stock markets, one influenced by the US market, the second influenced by the Japanese market, and the third having no link with the other markets. Contrary to Gosh *et al.*'s study, Yang *et al.* [21] report that the US markets affect Asian markets, whereas Chen *et al.* [22] report significant integration between US and Asian markets only during pre- and post-crisis periods.

For the recent financial crisis (2008–2009), Nikkinen *et al.* [23] report a segmentation of Baltic stock markets before the crisis and a significant link to European stock markets during the crisis. Orłowski [24] studied the proliferation of risks in US and European financial markets prior to and during the crisis. His results show important levels of volatility during financial distress and a significant increase of risk in only three markets: Germany, Hungary, and Poland. Kenourgios and Samitas [25] analyze long-term relationships between Balkan emerging markets and various developed markets during the global financial crisis. Their results show an increase of stock market dependence during the period of turmoil. Singh *et al.* [26] examined price and volatility spillovers across North American, European and Asian stock markets, finding an important regional influence among Asian and Europeans stock markets.

In this paper, we focus on studying the effect of the Global Financial Crisis on the intraday volatility transmission of three European markets (France, Germany, and the UK). The methodology of the study proceeds as follows. First, we identify the date of shock using the structured break test of Bai and Perron. Second, we apply the Flexible Fourier Form (FFF) procedure in order to use our high frequency 5 min intraday data and to deal with the problem of seasonality observed in intraday data. Then, after splitting our data into two periods according to the date of shock—pre-turmoil and turmoil—we study European markets returns by employing the bivariate vector autoregressive framework (VAR). According to this model, the returns of a given market are related to past returns of the same market and to the cross-market current and past returns in another market. Finally, we investigate the intraday volatility transmission by using an EGARCH model which captures the asymmetric impact of shocks on volatility.

This paper contributes to the existing literature on three fronts. First, papers such as [24–26] typically use daily data series to study financial crises, and their impact on market interrelation and risk. However, according to the literature and in comparison with daily data, high frequency data better explain the dynamic properties of volatility and their driving forces [27]. Our paper uses high frequency 5 minute intraday data to study the volatility interactions among equity markets and takes into account strong intraday seasonality observed in intraday data. Second, we use a more robust econometric technique to investigate the structural breaks in data, applying Bai and Perron methodology [28,29] to distinguish between calm and turbulent phases. Considering the two periods (calm and turbulent), the study makes an original contribution to understanding market behavior during the global financial crisis and the ongoing debate about financial market theory. The third major contribution of this paper is to provide empirical evidence, not only on the level of interdependence between European markets by applying a VAR and EGARCH framework to study cross-market return and volatility transmission during calm and turmoil periods, but also in investigating the phenomenon of contagion during the Global Financial Crisis through the study of magnitude of changes in volatility between the two periods.

The structure of the paper is organized as follows. Section 2 describes the data and specifies the turmoil period. Section 3 presents the econometric methodology used in the study. Section 4 reports and discusses the results and a final section concludes.

2. Data and Preliminary Analysis

For empirical analysis, we use two different data sets. First, we use Standard & Poor's 500 (S&P 500) daily index from 1 January 2004 to 31 December 2010 to identify the start date of the turmoil period, considered econometrically as the structural break in our data. S&P 500 price index was obtained from DataStream. Second, we use high frequency 5 min stock market price data of three stock markets, namely CAC40 (France), DAX30 (Germany), and FTSE100 (UK) from 1 July 2008 to 28 November 2008. Inspired by the event study methodology, and following the methodology used by many researchers (e.g., [30]), we use a narrow event window, only examining a short period surrounding the structural break (date of event) in order to provide a deeper insight into the spillover dynamics. We obtain high frequency data from Tick Data. They consist of 108 trading days and 10,710 observations for each index. Note that, if needed, we apply linear interpolation to replace solitary 5 min price quotes to obtain periodical data. The markets under study open and close at the same time, *i.e.*, 9.30 CET (Central European Time) and 17.30 CET, so we do not encounter overlapping problems in our study.

2.1. Turmoil Period Specification

To split our data into two periods (calm and turmoil periods), we need, as a first step, to specify the crisis phase. Many researchers determine the date of beginning of the crisis based on major economic and financial events [2,9,13]. This method is in some degree arbitrary [13]. Other researchers use the Markov regime switching models to distinguish between crisis and pre-crisis periods [13]. In this paper, we opt for the Bai and Perron test (BP) [28,29] because it clearly identifies the exact dates of structural break.

BP involves regressing the variable of interest on a constant and then testing for breaks within that constant. Therefore, it tests the null hypothesis—of no structural break—against a certain number of breaks. In our case, Bai and Perron may be presented as follows:

$$P_t = \theta_k + \varepsilon_t \quad t = Tk-1 + 1, \dots, Tk, \quad k = 1, \dots, m+1$$

where P_t is the stock market price index at time t , θ_k is the mean of the price in the k^{th} regime, m represents the length of the time series, and ε_t represents the error term. BP requires two parameters for its implementation. First, it requires the minimum number of observations between breaks and second, it requires maximum number of possible breaks.

According to our results, the date of Structural break is on Friday, 12 September 2008 with 95% confidence intervals. Note that on 15 September 2008, Lehman Brothers officially announced itself bankrupt and filed for bankruptcy protection. Markets seem to have already started to respond to the financial environmental uncertainty one trading day before the official announcement.

2.2. Data Analysis

Table 1 presents a summary of descriptive statistics of the stock index returns of French, German, and UK markets, categorized for whole period (from 1 July to 28 November 2008), during calm period (from 1 July to 11 September 2008), and the turmoil period (from 12 September to 28 November 2008). As expected, all returns are positive during the calm period, whereas these are negative during the turmoil episode. With regards to standard deviation, which indicates the level of volatility of data, they significantly increase after the structural break. Note that the skewness coefficients are positive for all countries except the UK during the calm period. Moreover, the coefficient indicates that distribution is more asymmetric during the crisis period than the calm period. Also, all indices returns exhibit excess kurtosis and rise substantially during the second period. This is evidence of the existence of extreme events. Furthermore, the Jacque-Bera test rejects the normality hypothesis for the three markets for all subsamples. Finally, all indices returns series are stationary and present ARCH effects (the results are not reported here).

Figure 1 shows the evolution of French, German and UK stock indices during the period from 1 July 2008 to 28 November 2008. The figure points out high co-movements among the three European indices during the whole period. From the graph, we can also see that the stock prices were relatively stable during the period from July 2008 to mid-September. After this date, we observe an important downward trend.

Figure 1. The evolution of European stock markets indices (1 July 2008 to 28 November 2008).

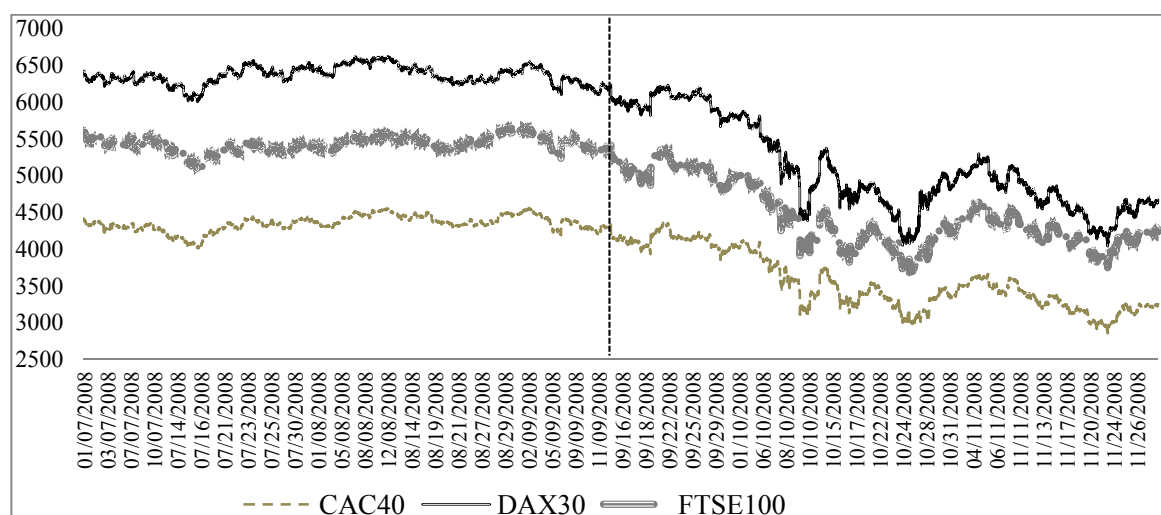
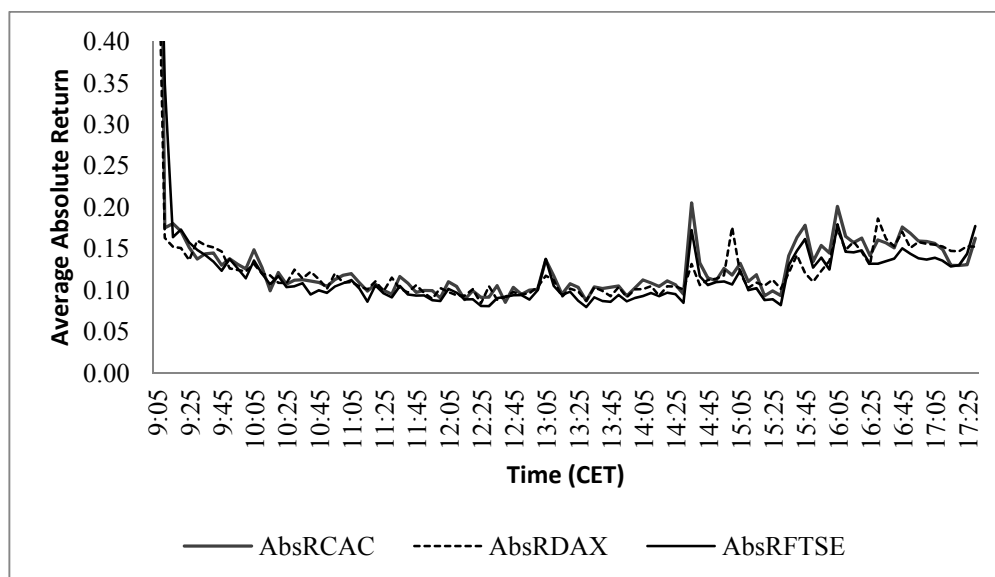


Figure 2 illustrates the evolution of average intraday volatility of stock markets indices estimated by absolute returns. Following the literature [31,32], we consider the absolute return $|R_{t,n}|$ as a measure of volatility. The figure shows clearly the strong structure of the volatility. The intra-daily volatility shows the U-shape identified for most of the markets, and suggested by the model of Admati and Pfleiderer [33], *i.e.*, a strong volatility at the beginning and end of the trading session. This falls back to a low level until 14.00 CET; afterwards, the activity on the market accelerates significantly with peaks between 14.00 and 15.00 CET.

Figure 2. Average intraday volatility evolution in stock markets indices (1 July 2008 to 28 November 2008).



Note: The graph shows the average at intervals of five minutes of Absolute Returns $|R_t|$ of CAC 40 (AbsRCAC), DAX 30 (AbsRDAX) and FTSE100 (AbsRFTSE) indices from July 2008 till the end of November 2008.

Figure 3 illustrates the average intraday volatility before and during the turmoil period. We can observe that, even if the U-shape has remained the same, there is, on average, stronger volatility after the break point. These graphs provide evidence of the presence of seasonal structures in our intra-daily data. In line with Andersen and Bollerslev [27–34] and in order to avoid potential biases, the series of intraday returns were deseasonalized.

Figure 3. Average intraday volatility before and during the turmoil period.

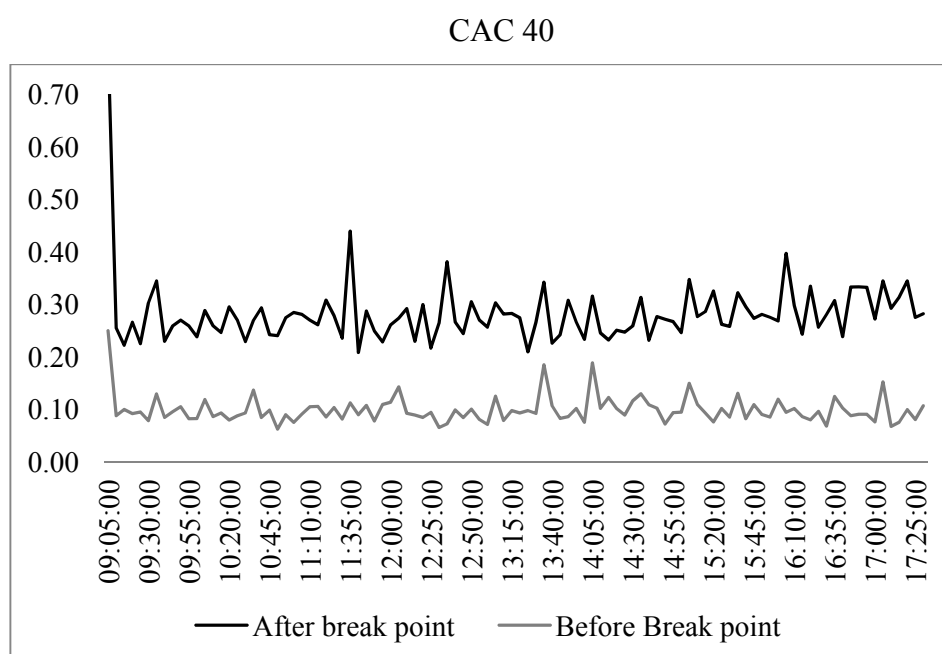
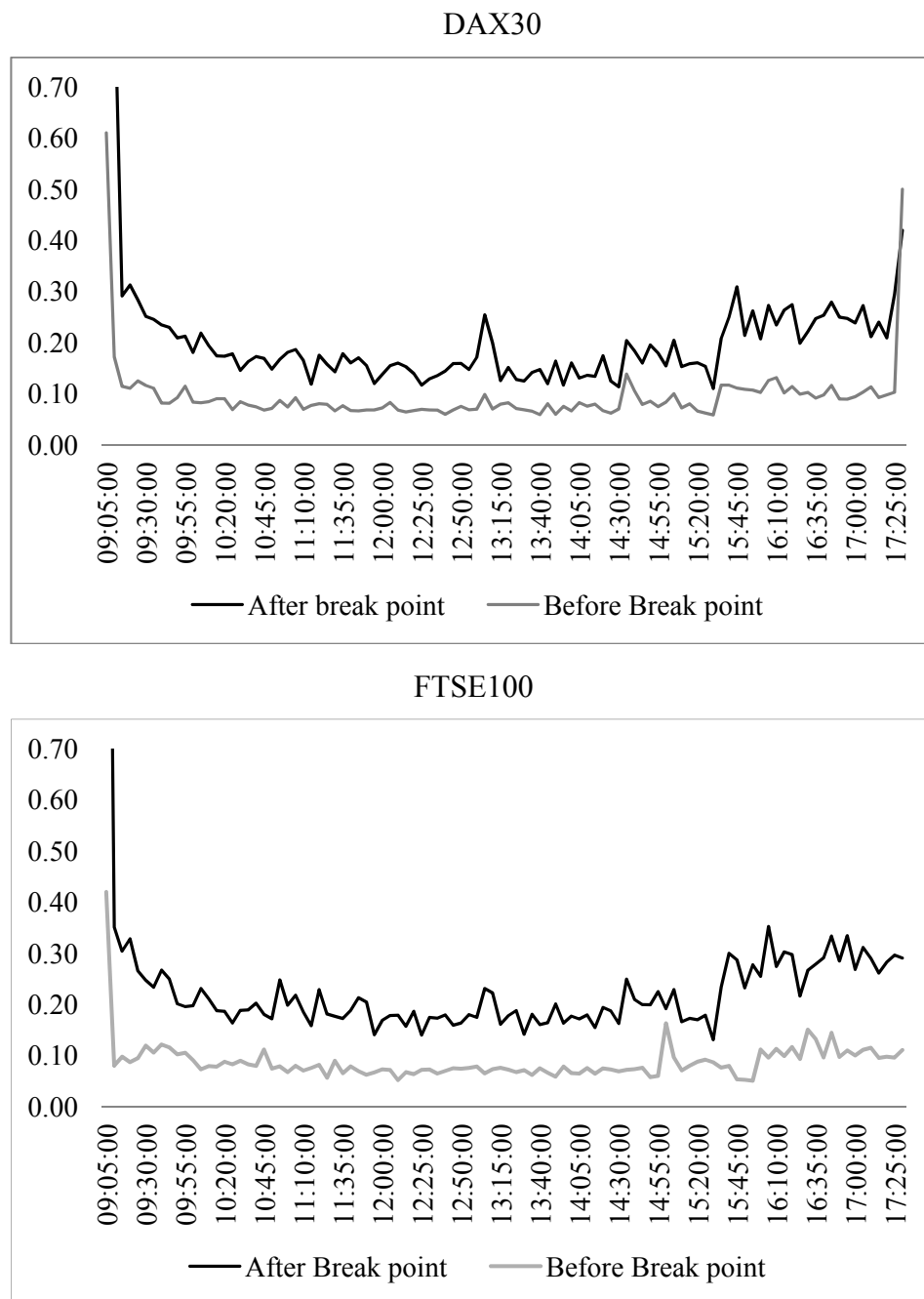


Figure 3. Cont.



3. Methodology Framework

Before studying the spillover dynamics of stock markets indices returns we should, first, deseasonalize and standardize our high frequency 5 minute intraday data, in order to eliminate outliers and other anomalies present in such data. Second, we apply a bivariate VAR-EGARCH model to investigate the volatility and market behavior of the three European markets.

Table 1. Descriptive statistics of data.

	Whole Period			Calm Period			Turmoil Period		
	1 July 2008 to 28 November 2008			1 July 2008 to 12 September 2008			13 September 2008 to 28 November 2008		
	RSCAC	RSDAX	RSFTS	RSCAC	RSDAX	RSFTS	RSCAC	RSDAX	RSFTS
Mean	−0.002332	−0.001905	−0.001426	0.000530	0.001422	0.000463	−0.005036	−0.005047	−0.003211
Median	−0.003149	−0.003858	−0.004682	−0.002501	0.000450	−0.002814	−0.004013	−0.009451	−0.008791
Maximum	2.768749	2.838545	2.900669	1.132326	1.395331	1.060863	2.768749	2.838545	2.900669
Minimum	−1.673299	−1.791665	−3.044328	−1.090163	−1.079340	−0.842513	−1.673299	−1.791665	−3.044328
Std. Dev.	0.232476	0.243903	0.226617	0.182200	0.185796	0.178694	0.271532	0.288201	0.264012
Skewness	0.103355	0.107824	0.093690	0.071269	0.050567	−0.034998	0.122225	0.133416	0.136466
Kurtosis	6.938096	7.023621	12.08220	4.948796	5.879413	4.397209	6.305681	6.051845	11.88740
Jarque-Bera	6939.780	7245.328	36825.20	827.5778	1799.296	424.2000	2521.581	2153.848	18144.36
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	10,710	10,710	10,710	5,202	5,202	5,202	5,508	5,508	5,508

This table shows the mean, the median, the maximum, the minimum, and the standard deviation (Std. Dev.) of stock indices returns. Note that these data are presented in a percentage format. The table also shows the skewness, the kurtosis coefficients and the normality test-Jarque-Bera test-of the three European Markets returns indices: the CAC40 (RSCAC), the DAX30 (RSDAX) and the FTSE (RSFTS). The data are provided for the whole period, the calm and the turmoil period.

3.1. Deseasonalization of Data via the Flexible Fourier Form (FFF)

We clean the high frequency stock price data for outliers and other anomalies before converting them into continuously compounded returns [35]. The methodology used is the Flexible Fourier Form (FFF) proposed by Gallant [36]. This methodology was advocated by Andersen and Bollerslev [27,34] and has the advantage of being practical and robust. The intraday volatility pattern is determined by modeling intervals of 5 min absolute returns. Following Andersen and Bollerslev [27,34], the following decomposition of the intraday returns is considered:

$$R_{t,n} = s_{t,n} \times \sigma_t \times N^{-1/2} \times Z_{t,n} \quad (1)$$

where N refers to the number of high-frequency returns per day, σ_t captures the overall volatility level on day t , s_t denotes the periodic intraday volatility component, and $Z_{t,n}$ is an independent and identically distributed (iid) with zero mean and unit variance error term. $X_{t,n}$ is then defined as:

$$X_{t,n} = \frac{|R_{t,n}|}{\sigma_{t,n} N^{\frac{1}{2}}} \quad (2)$$

Replacing σ_t by an estimate from a daily realized [37] volatility, \hat{X} was obtained. The seasonal pattern was estimated by using ordinary least square estimation (OLS).

$$\hat{X}_{t,n} = f(\theta; t, n) + \mu_{t,n} \quad (3)$$

with

$$f(\theta; t, n) = C + N_1 \frac{n}{(N+1)/2} + N_2 \frac{n^2}{(N+1)(N+2)/6} + \sum_{p=1}^P A_p \sin(2\pi p n / N) + \sum_{p=1}^P B_p \cos(2\pi p n / N) \\ + \mathcal{I}_{Open} + \mathcal{I}_{Close} + \mathcal{I}_{OpenUS} \quad (4)$$

P indicates the order of the expansion, i.e., the number of sinusoids necessities to reproduce the profile of the modeled variable. *OPEN*, *CLOSE* and *OpenUS* are dummy variables which characterize respectively the effect of opening at 9.05 am CET for the European market, 5.30 pm CET close for the European market and at 3.30 pm CET for the US market opening.

The deseasonalized and standardized intraday returns were then obtained respectively by:

$$\tilde{R}_{t,n} \equiv R_{t,n} / \hat{f}_{t,n} \quad (5)$$

$$\hat{R}_{t,n} \equiv R_{t,n} / \hat{\sigma}_t \hat{f}_{t,n} \quad (6)$$

3.2. Bi-Variate VAR EGARCH Process

We consider the EGARCH framework introduced by Nelson [38]. This model performs the GARCH model of Bollerslev [30], mainly due to the fact that it imposes no positivity constraints on estimated parameters and captures the asymmetric effect on volatility [39]. This so called *leverage effect* means that positive and negative error terms have an asymmetric effect on the volatility. Hence, the volatility increases more after bad news than after good news.

We use a bivariate VAR-EGARCH model to investigate the volatility of our series of returns of the CAC40, the DAX30 and FTSE100 indices.

The VAR(k)-EGARCH (1,1) model is given in the following way:

$$R_{i,t} = \beta_{i,0} + \sum_{j=1}^n \sum_{m=1}^k \beta_{i,j} R_{j,t-m} + \varepsilon_{i,t} \quad (7)$$

with $i = 1, \dots, n$ and refers to the stock market index.

Equation (7) is a vector autoregressive (VAR) model of the conditional mean equation of returns on stock market index i ($R_{i,t}$). It means that R_i depends on previous own values of stock returns i (R_i), the cross-market current and past returns (R_j) and the random variable (ε_i). The random variable is conditionally Gaussian,

$$\varepsilon_t | I_{t-1} \sim N(0, h_t)$$

with I_{t-1} the information set containing intradaily price information through period $t - 1$, and the diagonal elements of the conditional variance h_t may be given as follows:

$$\ln(h_{i,t}) = \alpha_{i,0} + \sum_{j=1}^n \alpha_{i,j} (|Z_{j,t-1}| - E(|Z_{j,t-1}|)) + \gamma_{i,j} Z_{j,t-1} + \delta_{i,j} \ln(h_{i,t-1}) \quad (8)$$

where $Z_t = \varepsilon_t / \sqrt{h_t}$ is the standardized innovation and $E(|Z_t|) = \sqrt{2/\pi}$.

The second equation of the model (Equation (8)) represents the conditional variance of the stock market index returns. This equation means that the exponential conditional variance depends on the lagged value of innovation of the stock returns, the terms to capture asymmetric effects, and lag of conditional variance of the stock market return index. The parameters $\alpha_{i,j}$ with $i = j$ captures the effect of the magnitude of a lagged innovation on the conditional variance, and when $i \neq j$ the coefficient captures the size and sign effect of a shock to market j on market i . Further, γ captures the effects of news from the stock market on the conditional variance (the leverage effect). Hence, γ allows volatility to react differently accordingly to the sign of lagged returns (positive *versus* negative). If γ is negative and statistically significant, then we have an asymmetric response, *i.e.*, the effect of bad news will be larger than good news. The last parameter δ measures the persistence of volatility in the stock market index returns.

4. Results and Discussion

4.1. FFF Estimates

The periodic character of the behaviour of the volatility inside the day of exchange is clearly illustrated via the correlative structure of autocorrelation of absolute returns [40] in Figure 4. As can be seen, the autocorrelations of the absolute returns on 10 days present systematic peaks for lags which correspond to the whole period.

The origin of this stylised feature was the intraday seasonality shown in Figure 2. As we can denote, the FFF representation considerably reduced the intraday periodicity. As shown in the Figure 4, there is a significant decay in serial correlation. Therefore, the standardized returns are reducing the risk of

spurious causality. Once the data are deseasonalized and combined, in order to remove the periodicity, we obtain contemporaneous 5-min filtered returns.

Once problems of outliers and periodicity have been addressed using FFF estimates, we can use our filtered and corrected data to investigate return and volatility spillover using the bivariate VAR-EGARCH estimates.

Figure 4. Autocorrelation of intraday absolute and deseasonalized index returns.

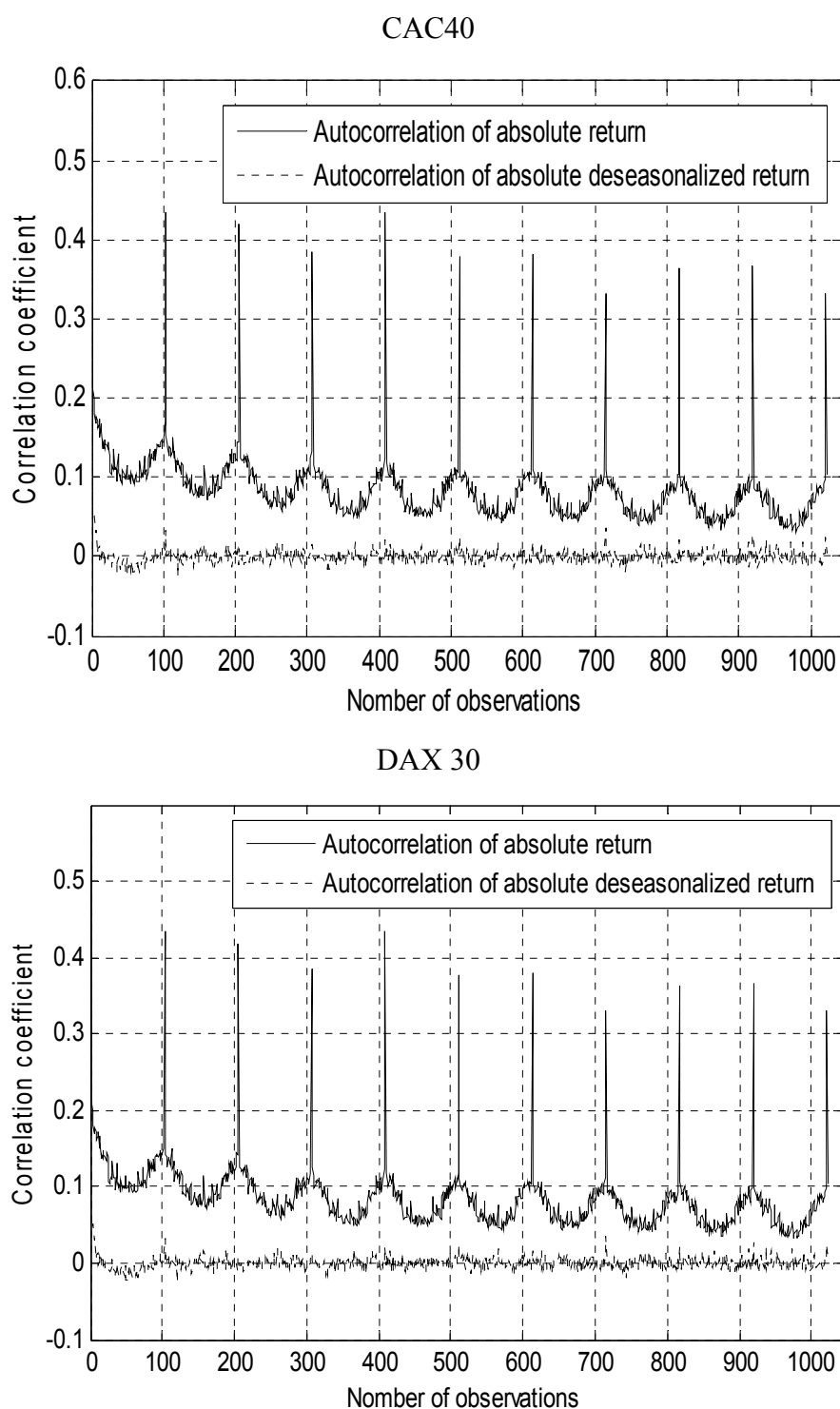
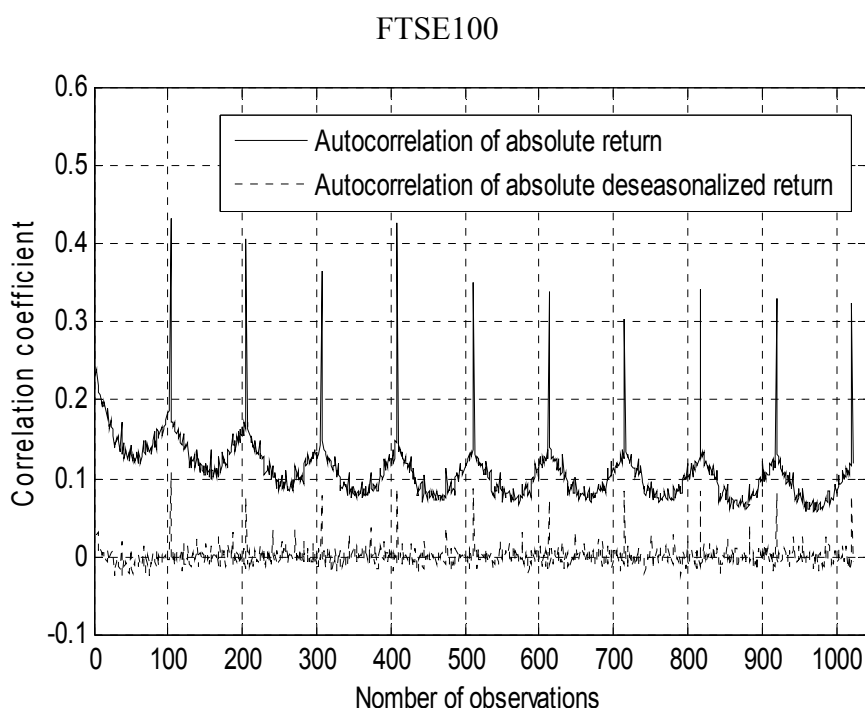


Figure 4. Cont.



Note: The maximum lag length shown on horizontal axis is 10 days. The solid line represents the autocorrelations coefficients for absolute returns and the dotted line the autocorrelations coefficients for absolute deseasonalized returns.

4.2. Modeling Intraday Volatility Specifications and Analysis—Bivariate VAR-EGARCH Estimates

We proceed with the estimation of the bivariate VAR-EGARCH model among the pairs of indices of: CAC40/DAX30, the CAC40/FTSE100 and the DAX30/FTSE100. Estimation results are reported in Tables 2–4. The model specification is chosen according to likelihood ratio tests and the minimum value of the information criteria, while the lag order is selected by Akaike (AIC) and Schwarz (SIC) information criteria [41].

For all pairs of indices, we note that, in most cases, the parameters of the model are statistically significant. These results provide evidence of return and volatility spillover among these markets. Note, however, that the levels of transmission of returns and volatility depend on both the pairs of markets and the period of study considered. Moreover, the estimated γ coefficients for the asymmetry effect are significant at the 5% level, which indicate the existence of an asymmetric response of volatility to shocks and justifies the use of EGARCH model. In the following sections, we analyse the return and volatility transmission according to each period in order to investigate the interrelationship among these European markets surrounding the break date.

4.2.1. Market Behaviour during the Calm Period

The VAR terms ($\beta_{i,j}$) are estimated from the conditional mean equation of returns Equation (8). According to Tables 2–4, the estimated $\beta_{1,2}$ and $\beta_{2,1}$ coefficients indicating respectively the return transmission from market 2 to market 1 and from market 1 to market 2 are statistically significant.

This result shows that there is a significant return spillover between the markets, a finding in line with previous research (e.g., [38]).

Moreover, the results indicate a more significant return spillover from DAX30 to both the CAC 40 and FTSE100, rather than the opposite. For example, considering the pair of indices DAX30/FTSE100, the parameter $\beta_{1,2}$ is not significant, whereas the parameter $\beta_{2,1}$ is significant and equal to 0.1516, suggesting that roughly 15.16% of the German returns innovation is transferred to the UK stock market.

Table 2. VAR (1) EGARCH (1,1) CAC 40 FTSE 100 estimates.

Variable	Before 12 September 2008			After 12 September 2008		
	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
$\beta_{1,0}$	0.0001	0.0013	0.0594	−0.0068 **	0.0031	−2.2115
$\beta_{1,1}$	−0.0980 ***	0.0203	−4.8173	−0.1269 ***	0.019	−6.6757
$\beta_{1,2}$	0.1253 ***	0.023	5.4433	0.1255 ***	0.0184	6.8089
$\beta_{2,0}$	0.0003	0.0018	0.1959	−0.0053 *	0.0029	−1.8372
$\beta_{2,1}$	0.0409 **	0.02	2.0482	0.0340 *	0.0187	1.8172
$\beta_{2,2}$	−0.0081	0.0223	−0.3648	0.0118	0.017	0.6939
$\alpha_{1,0}$	−0.6520 ***	0.0788	−8.2732	−0.1839 ***	0.0306	−6.017
$\alpha_{1,1}$	0.0732 ***	0.0207	3.5432	0.1598 ***	0.0191	8.3607
$\alpha_{1,2}$	0.1141 ***	0.0213	5.3674	0.0845 ***	0.0149	5.6717
$\alpha_{2,0}$	−0.5698 ***	0.0062	−91.7875	−0.1912 ***	0.0299	−6.4019
$\alpha_{2,1}$	0.0558 ***	0.0171	3.2598	0.2253 ***	0.0196	11.4981
$\alpha_{2,2}$	0.1050 ***	0.0203	5.1841	0.0460 ***	0.0146	3.1477
γ_{12}	0.5602 *	0.3016	1.8571	−0.0938 ***	0.033	−2.8477
γ_{21}	−0.4119 **	0.1643	−2.5075	−0.2250 ***	0.0828	−2.7162
δ_1	0.8087 ***	0.0229	35.2466	0.9287 ***	0.0115	80.783
δ_2	0.8344 ***	0.0024	353.2126	0.9278 ***	0.011	84.6729
ρ	0.8060 ***	0.0046	174.3189	0.8329 ***	0.0036	232.3012
$Q_{CAC}(20)$	27.60	<i>p</i> -value 0.119		24.612	<i>p</i> -value 0.326	
$Q_{FTSE}(20)$	29.155	<i>p</i> -value 0.098		26.054	<i>p</i> -value 0.128	
$Q^2_{CAC}(20)$	25.661	<i>p</i> -value 0.130		21.739	<i>p</i> -value 0.344	
$Q^2_{FTSE}(20)$	21.525	<i>p</i> -value 0.202		21.441	<i>p</i> -value 0.550	

Note: Data are obtained using 5 min deseasonalized and standardized returns. $\beta_{i,j}$ are coefficients of the regression of the VAR equation—conditional mean equation of returns (Equation (7)). The specification and optimal lags of the VAR equation are chosen according to likelihood ratio tests and Akaike (AIC) and Schwarz (SIC) information criteria, respectively. The coefficients α , γ and δ are coefficients of the regression of the conditional variance of returns (Equation (8)). The asymmetric terms γ are statistically significant which confirms the use of EGARCH model. The Q-test of correlation $Q(20)$ and $Q^2(20)$ does not reject the null hypothesis of no serial correlation (using 20 lags). CAC40 refers to market 1 and FTSE100 to market 2. *, **, *** represent statistical significance at 10%, 5% and 1% respectively.

Table 3. VAR (1) EGARCH (1,1) DAX 30 FTSE 100 estimates.

Variable	Before 12 September 2008			After 12 September 2008		
	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
$\beta_{1,0}$	0.0009	0.0025	0.3609	−0.0051 *	0.0031	−1.667
$\beta_{1,1}$	0.0166	0.0209	0.7939	−0.0639 ***	0.0163	−3.9165
$\beta_{1,2}$	0.0011	0.0212	0.0508	0.0318 **	0.0161	1.9744
$\beta_{2,0}$	0.0006	0.0024	0.2618	−0.0035	0.003	−1.1677
$\beta_{2,1}$	0.1516 ***	0.0197	7.6869	0.0941 ***	0.0164	5.734
$\beta_{2,2}$	−0.0915 ***	0.0206	−4.4342	−0.0411 **	0.0174	−2.3638
$\alpha_{1,0}$	−0.5183 ***	0.0963	−5.3824	−0.0869 ***	0.0141	−6.1684
$\alpha_{1,1}$	0.1373 ***	0.0208	6.5894	0.1705 ***	0.0147	11.6273
$\alpha_{1,2}$	0.0323	0.0205	1.5715	0.0165	0.0117	1.4082
$\alpha_{2,0}$	−0.4229 ***	0.0792	−5.3407	−0.1270 ***	0.0209	−6.0909
$\alpha_{2,1}$	0.0758 ***	0.0182	4.152	0.1795 ***	0.0161	11.1249
$\alpha_{2,2}$	0.0859 ***	0.0209	4.109	0.0681 ***	0.0123	5.53
γ_{12}	−0.049	0.0754	−0.6501	−0.1301 ***	0.0393	−3.3083
γ_{21}	−0.1007	0.0931	−1.0824	−0.0314 *	0.1092	−1.9881
δ_1	0.8452 ***	0.0285	29.6699	0.9639 ***	0.0055	174.1163
δ_2	0.8770 ***	0.0228	38.4051	0.9508 ***	0.0077	122.8481
P	0.7521 ***	0.0059	127.4695	0.7783 ***	0.0051	151.5845
$Q_{DAX}(20)$	29.602	<i>p</i> -value 0.091		23.048	<i>p</i> -value 0.112	
$Q_{FTSE}(20)$	27.648	<i>p</i> -value 0.150		20.226	<i>p</i> -value 0.323	
$Q^2_{DAX}(20)$	18.812	<i>p</i> -value 0.564		12.377	<i>p</i> -value 0.749	
$Q^2_{FTSE}(20)$	17.303	<i>p</i> -value 0.627		19.255	<i>p</i> -value 0.315	

Note: Data are obtained using 5 min deseasonalized and standardized returns. β_{ij} are coefficients of the regression of the VAR equation—conditional mean equation of returns (Equation (7)). The specification and optimal lags of the VAR equation are chosen according to likelihood ratio tests and Akaike (AIC) and Schwarz (SIC) information criteria, respectively. The coefficients α , γ and δ are coefficients of the regression of the conditional variance of returns (Equation (8)). The asymmetric terms γ are statistically significant which confirms the use of EGARCH model. The Q-test of correlation $Q(20)$ and $Q^2(20)$ does not reject the null hypothesis of no serial correlation (using 20 lags). CAC40 refers to market 1 and FTSE100 to market 2. *, **, *** represent statistical significance at 10%, 5% and 1% respectively.

Table 4. VAR (2) EGARCH (1,1) CAC 40 DAX 30 estimates.

Variable	Before 12 September 2008			After 12 September 2008		
	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
$\beta_{1,0}$	−0.0003	0.0022	−0.1555	−0.0045 *	0.0025	−1.8015
$\beta_{1,1}$	−0.2742 ***	0.0248	−11.0468	−0.1438 ***	0.0189	−7.5974
$\beta_{1,2}$	−0.0810 ***	0.0245	−3.3041	0.1649 ***	0.0171	9.655
$\beta_{1,3}$	0.3156 ***	0.0231	13.6933			
$\beta_{1,4}$	0.0475 *	0.025	1.904			
$\beta_{2,0}$	0.0003	0.0023	0.1407	−0.0050 *	0.0026	−1.8952
$\beta_{2,1}$	−0.0375	0.0251	−1.4949	0.0442 **	0.0184	2.4
$\beta_{2,2}$	−0.0217	0.025	−0.868	−0.0767 ***	0.0167	−4.5822
$\beta_{2,3}$	0.0441 *	0.0228	1.93			
$\beta_{2,4}$	−0.002	0.0264	−0.0761			
$\alpha_{1,0}$	−0.5982 ***	0.0898	−6.6635	−0.0251 ***	0.0097	−2.5853
$\alpha_{1,1}$	0.0373 *	0.0224	1.661	0.0047 ***	0.0007	7.1456
$\alpha_{1,2}$	0.1748 ***	0.0249	7.014	0.1107 ***	0.0094	11.7436

Table 4. Cont.

Variable	Before 12 September 2008			After 12 September 2008		
	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
$\alpha_{2,0}$	−0.6357 ***	0.1367	−4.6502	−0.0204 **	0.009	−2.2539
$\alpha_{2,1}$	0.0044	0.023	0.1928	0.0046 ***	0.0007	6.954
$\alpha_{2,2}$	0.1951 ***	0.0272	7.1742	0.1141 ***	0.0082	13.9236
γ_{12}	0.1976	0.2764	0.715	−11.135 ***	0.0785	−141.822
γ_{21}	−0.0893 *	0.0504	−1.7731	0.2671 ***	0.0486	5.5001
δ_1	0.8249 ***	0.026	31.7162	0.9894 ***	0.0036	276.041
δ_2	0.8099 ***	0.0404	20.0285	0.9908 ***	0.0034	287.5268
ρ	0.8341 ***	0.0038	221.2988	0.8283 ***	0.0044	188.0018
$Q_{CAC}(20)$	27.665	p-value 0.073		25.433	p-value 0.209	
$Q_{DAX}(20)$	29.377	p-value 0.059		23.058	p-value 0.310	
$Q^2_{CAC}(20)$	32.485	p-value 0.052		21.739	p-value 0.363	
$Q^2_{DAX}(20)$	25.211	p-value 0.197		26.162	p-value 0.215	

Note: Data are obtained using 5 min deseasonalized and standardized returns. β_{ij} are coefficients of the regression of the VAR equation—conditional mean equation of returns (Equation (7)). The specification and optimal lags of the VAR equation are chosen according to likelihood ratio tests and Akaike (AIC) and Schwarz (SIC) information criteria, respectively. The coefficients α , γ and δ are coefficients of the regression of the conditional variance of returns (Equation (8)). The asymmetric terms γ are statistically significant which confirms the use of EGARCH model. The Q-test of correlation $Q(20)$ and $Q^2(20)$ does not reject the null hypothesis of no serial correlation (using 20 lags). CAC40 refers to market 1 and FTSE100 to market 2.

*, **, *** represent statistical significance at 10%, 5% and 1% respectively

As regards the intraday volatility spillover (Equation (9)), the estimated $\alpha_{1,2}$ and $\alpha_{2,1}$ coefficients indicate respectively the volatility transmission from market 2 to market 1 and from market 1 to market 2. For example, considering the pair of indices CAC40/FTSE100 (Table 2), the volatility of the French market is explained at 11.41% by the volatility of the UK market, whereas only 5.58% of UK volatility that is explained by the French market. These coefficients are mostly statistically significant, which provides evidence that the conditional variance in each market is affected by “innovations” emanating from the other markets. Note, however, that the French and the UK markets seem to be more influenced by the German market in term of volatility, whereas the reverse is less pronounced. These findings provide strong evidence that markets are inter-related during relatively stable times, pointing out the interdependence phenomenon between them.

4.2.2. Markets Behaviour during the Turmoil Period

Turning to the turmoil period the analysis reveals, first, that the coefficients of asymmetry (γ_{ij}) are significant during this period. This result is not surprising, as during the turbulent period good news may have a bigger impact than negative news, unlike what happens during calm periods. The (δ_i) coefficients, which measure the impact of all past shocks on the current conditional variance, are also highly significant and approach one during the turbulent period. This result is expected as the markets are in a continuous process of turbulence and the clustering phenomenon is observed.

Second, the estimated coefficients indicating the return ($\beta_{1,2}$ and $\beta_{2,1}$) and the volatility ($\alpha_{1,2}$ and $\alpha_{2,1}$) transmission are mostly statistically significant. These results can confirm the strong interrelationship among markets during turmoil period.

Third, we observe that the German market continues to influence returns and volatility of British and French markets. Hence, up to 9.41% and to 16.49% of respectively the returns of FTSE100 and CAC40 indices are explained by German market. Considering the volatility behavior, around 17.95% of British market volatility is affected by German market. The impact is relatively less important on French market, where the volatility spillover coefficient $\alpha_{1,2}$ is equal to 11.07%.

Focusing on the level of correlation of returns (ρ) between the markets, it increased after the break date—except for the French-German pair, where the correlation remains relatively constant; the coefficient between German and UK indices rose from 0.75 to 0.78, and from 0.8 to 0.83 for the French and UK indices. These results confirm those of Forbes and Rigobon [2], and Ahlgren and Antell [42] who show that markets are inter-related. Following a crisis or a shock to one country, we generally observe a significant increase in these cross-market linkages and correlations.

A comparative analysis between calm and turmoil periods shows that, with regards to return spillover, the magnitude of transmission is roughly the same between the two periods. However, in term of volatility spillover, the transmission was more important during turmoil periods. Our findings do not offer evidence of contagion induced by the crisis. The increase of volatility after the structural break seems to be induced mainly by the interdependence of markets due to normal linkages between them. These results also confirm previous studies showing that European markets were deeply affected by US market and shocks emanating from it, which had led to the Global Financial Crisis, e.g., [18]. Moreover, the interrelationship of these European markets was characterized especially by the influence of the German market on French and UK markets during the whole period of study, and which increased during turmoil period. This could be explained by the overall composition of the DAX index as well as the financial and real channels of transmission. Another possible interpretation is linked to herding behavior on French and UK markets. It seems that German market is seen as the leader in the Euro Zone, probably due to the fact that it is the world's fourth largest national economy (after the USA, Japan, and China) and is furthermore the most important market in the European Union. Moreover, as was highlighted by many economists and policy makers, the German economy was the largest contributor to stopping the Eurozone to falling back into recession during the global financial crisis [43,44]. Hence, it seems that during turmoil periods, a greater attention is given by European investors to German financial market behavior.

5. Conclusions

This article studies stock market volatility behavior of three European markets, *i.e.*, France, Germany, and the UK, by analyzing intraday volatility transmission among them during the stocks market collapse in 2008. To do that, we deseasonalized data using the Flexible Fourier Form and segmented it into calm and turbulent periods based on the break date (September 12, 2008) estimated using the Bai-Perron procedure.

The analysis of correlation coefficients shows that the three indices—the DAX 30, CAC 40, and FTSE 100—are highly intercorrelated, and that these correlations become slightly more important

during the turbulent period. These results support a general pattern of coupling for the three markets during the whole period of study, with an increase in the coupling during the turmoil phase. This argument is further supported by the findings of Dimitriou *et al.* [16]. Moreover, our analysis provides insights into interdependence structures, intraday return and volatility spillover during the whole period of study. We also find that, in terms of return spillover between European markets, the magnitude of transmission is roughly the same between the two periods. Conversely, in term of volatility spillover, the transmission was more important during turmoil periods. These findings support the hypothesis that cross-market interactions and dependency are stronger during market downturns than market upturns [15]. However, the results do not allow us to conclude to the existence of a pattern of contagion for all markets. The increase of volatility during turmoil period seems to be mainly due to the interdependence of markets.

Focusing on return and volatility behavior stock markets, we also found that German market influences French and UK markets, especially during turmoil period. Germany seems to have been seen as the hub of financial and economic activity in Europe during the period of study. These findings raise question concerning the role of market consensus *versus* information during periods of stress. It would be interesting to incorporate these effects in the empirical modeling to study the behavior of exchange volatility during the extreme turbulent periods.

Our findings have implications for international investors. Evidence on deep interdependence between European markets calls into question the advantages of investing in multiple European markets in order to diversify a portfolio, especially during turmoil periods. On the other hand, since European markets seem to be widely influenced by German market, special attention should be given by those who invest in Europe to the economic, financial, and political prospects of Germany.

The results also provide implications for European policy makers about the decisions and directions to take to better protect markets from contagion and financial collapse. They should examine the possible strategies to reduce the inter-relationships between markets, and especially to mitigate, as far as possible, German influence. These findings can also be relevant to Asian policy makers debating the advantages and disadvantages of increasing financial integration in the region.

In such a financial context—becoming more and more integrated—there is a great interest in identifying potential gains from international portfolio diversification. This should lead to the development of more in-depth studies focusing on stock market relationships. Future research could better explain the role of investor behavior in interdependence of financial markets and impact of the crisis.

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Conflict of Interest

The authors declare no conflict of interest.

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