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Terrorism induced cross-market transmission of shocks: A case study using intraday data

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TERRORISM INDUCED CROSS-MARKET TRANSMISSION OF SHOCKS: A CASE STUDY USING INTRADAY DATA

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Abstract: Terrorist incidents exert a negative, albeit generally short-lived, impact on markets and equity returns. Given the integration of global financial markets, mega-terrorist events also have a high contagion potential with their shock waves being transmitted across countries and markets. This paper investigates the cross-market transmission of the London Stock Exchange’s reaction to the terrorist attacks of 2005. It focuses on how this reaction was transmitted to two other major European stock exchanges: Frankfurt and Paris. To this effect, high frequency data are used and multivariate GARCH models are employed. Findings reported herein indicate that the volatility of stock market returns is increased in all three cases.

JEL Classification: H56, G1, G15
Key Words: terrorism, capital markets, contagion, multivariate GARCH

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1. Introduction

The high velocity with which the shock waves from major financial episodes, irrespective of the source that has generated them, travel across markets and countries has attracted increasing attention in the relevant financial literature. A plethora of studies, a survey of which can be found in Pericoli and Sbracia (2003), have examined both on a theoretical as well as empirical level the mechanisms and the channels through which financial shocks that occur in one country are transmitted and affect markets in another or indeed, have a major international impact on global markets and economic sentiment (inter alia: Meric and Meric, 1997; Goetzmann, et al., 2001; Cappiello, et al., 2006; Serwa and Bohl, 2005; Asimakopoulos et al. 2000). In particular, a number of studies have examined the interdependence of equity market volatility using the framework of autoregressive conditional heteroskedasticity (GARCH) time series models (inter alia: Hamao et al., 1990; Theodossiou and Lee, 1993; Lin et al., 1994; Longin and Solnik, 1995); while Forbes and Rigobon (2002) stress the need to distinguish between contagion and interdependencies. This can be done empirically by testing whether or not cross-market correlation increase statistically significantly in crises periods (inter alia: Syllignakis and Kouretas, 2011; Chiang et al. 2007).

A strand of the aforementioned literature, has focused on how markets react to exogenous events and shocks including natural or anthropogenic catastrophes and accidents, political risk and violent events such as conflict and terrorism (inter alia: Kaplanski and Levy, 2010; Capelle-Blancard and Laguna, 2009; Bolak and Suer, 2008; Asteriou and Siriopoulos, 2003; Bilson et al. 2002; Herbst et al. 1996; Bowen et al. 1983). The contagion potential of
such exogenous events has also been the subject of empirical investigation (\textit{inter alia}: Blose \textit{et al.} 1996; Kalra, 1995). Following mega-terrorist events such as for instance 9/11 in New York, and the Madrid and London bomb attacks of 2004 and 2005 respectively, the studies that turned to examine the impact that terrorism exerts on the economy in general and on financial markets in particular, has steadily grown (\textit{inter alia}: Eldor and Melnick, 2004; Amelie and Darne, 2006; Fernandez, 2008; Arin \textit{et al}. 2008; Nikkinen \textit{et al}. 2008; Barros and Gil-Alana, 2009; Nikkinen and Vahamaa, 2010; Brownrn and Derwall, 2010; Ramiah \textit{et al}. 2010). As it has been pointed out in a number of previous papers (\textit{inter alia}: Chen and Siems, 2004; Drakos, 2010a; Kollias \textit{et al}. 2011a, 2011b; Chesney \textit{et al}. 2011) although the threat of a terrorist attack is omnipresent, particularly in countries that are or have in the past been the victims of systematic and continuous terror campaigns, such as for instance Spain, Israel or the UK; terrorist events when they occur are unforeseen and, depending among others on their magnitude in terms of victims and/or damages or target(s) hit, have the potential to shake and rattle markets and investors. Just as in the case of natural or anthropogenic catastrophes and accidents, terrorist attacks are unanticipated and hence market agents cannot hedge against them. Such incidents can also have a high contagion potential as studies that have addressed this question and the channels of the cross-market transmission of terrorist induced shocks have shown (\textit{inter alia}: Hon \textit{et al}. 2004; Mun, 2005; Drakos, 2011, 2010b). Factors that seem to affect the transmission potential of such exogenous shocks from the market of the country that has been targeted by the terrorists to others include the degree of bilateral integration between the stock markets and the
degree of integration into the global economic and financial markets (Drakos, 2011, 2010b).

Within this particular thematic focus of this strand of literature, this paper addresses the cross-market transmission of the shock generated by a major European terrorist event. The study focuses on the July, 7th 2005 London bomb attacks that, along with the 2004 Madrid bombings, are considered to be the European equivalent of 9/11 albeit on a much smaller scale in terms of the number of victims and destruction to property and infrastructure (Kollias et al. 2011b).

However, unlike previous studies that mostly rely on daily data to assess the impact of terrorist events on financial markets as well as their contagion effect, this study uses high frequency intraday data to investigate the issue at hand in line with a growing number of papers that focus on the interdependence among stock markets through the use of intraday day data (inter alia: Connolly and Wang, 2003; Jones et al., 2005; Hanousek, 2009; Égert, and Kočenda, 2007)1. In particular, this paper examines how two other major European stock markets – Paris and Frankfurt – were affect by the July, 7th 2005 mega-terrorist attack in London. In the section that follows we proceed with the presentation of the data and the methodology employed. In section three, the findings are presented and discussed, while section four concludes the paper.

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1 For studies investigating interdependence among currencies using intraday data see for instance Engle et al., 1990; Baillie and Bollerslev, 1990; Hong, 2001; Elyasiani and Kogacil, 2001; Tse and Tsui , 2002; Kitamoura, 2010; Bubák et al., 2011. While for listed and unlisted stock reactions intraday see Markelos et al. (2003).
2. Data and Methodology

The July, 7th 2005 London terrorist incident, was a series of coordinated bomb blasts that hit the city’s public transport system during the morning rush hour. The suicide bombings, killed 52 commuters, injured 700, and caused extensive and widespread disruption of the city’s transport system and the country's mobile telecommunications infrastructure. As the results reported by Kollias et al. (2011b) show, the London Stock Exchange (henceforth LSE) suffered significant negative abnormal returns on the day of the attack. Both the general as well as sectoral indices seem to have been negatively affected by the event. However, this impact was rather short lived since the market quickly recovered and rebounded. Market volatility was also significantly affected but again, this was of a transitory nature (Kollias et al. 2011b).

As noted above, the aim of this paper is to investigate whether or not contagion between financial markets can be established in the case of this major terrorist incident that took place in a city that is one of the most important financial and trading centres of the world. Given LSE’s significance since it is one of the major financial markets globally with a market capitalisation well over 3,000,000 millions $2, one would intuitively expect that the shock waves could have been transmitted to other major European markets (Hsin, 2004). The possible contagion and shock transmission is examined through the use of multivariate GARCH models.

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2 LSE was the bigger in terms of market capitalization in 2005, in Europe followed by the German and French markets (see: www.world-exchanges.org/statistics).
Apart from the London stock exchange, our data set consists of intraday data for the German and French stock market returns over the period 21/01/2005 to 28/10/2005. These three countries are generally considered to be the most important economies in Europe with large and mature stock markets. The German stock returns are calculated from the DAX-30 index, the UK returns from the FTSE-100 index, and the French returns from the CAC-40 index. An advantage stemming from the use of intraday data over a short time period is that the possibility of structural breaks is much smaller compared to a longer time period needed if daily data was employed (Hassan and Malik, 2007). Indeed, the multivariate GARCH model might give inaccurate forecasts if the underlying process which generates asset prices undergoes a structural break. Moreover intraday data capture all the main features of the data generating process. In our case the bivariate unrestricted BEKK-GARCH(1,1) model, proposed by Engle and Kroner (1995), is used to investigate any possible contagion effects between the London, the German and the French stock markets on the day of the terrorist attack in question. What will be examined is whether or not and to what extent this terrorist event affected the volatilities and the correlation of the stock markets in questions using intraday data given the generally short lived effects of terrorism on markets as previous studies have shown with the use of daily data (inter alia: Fernandez, 2008; Nikkinen et al. 2008; Barros and Gil-Alana, 2009; Ramiah et al. 2010; Drakos, 2010a; Kollias et al. 2011b). In order to avoid any severe convergence problems (Bauwens et al. 2006), the bivariate unrestricted version of the general BEKK(p,q)-GARCH model with p=q=1 is used:
\[ R_{i,t} = \mu_i + \varepsilon_{i,t} \]  

with \( \varepsilon_t | \Phi_{t-1} \sim N(0, H_t) \) and

\[ H_t = C_0 C_0' + A \varepsilon_{t-1}' \varepsilon_{t-1} A + B' H_{t-1} B \]  

Where equation (1) gives the expression for the conditional mean; \( R_{i,t} \) and \( \varepsilon_{i,t} \) are the return vector (\( i=1 \) for the FTSE-100 index and 2 for the other two indices for each estimation), and the residual vector respectively; and \( \mu_i \) is the mean of this process. In equation (2) \( H \) is the conditional variance-covariance matrix that depends on its past values and on past values of \( \varepsilon_{i,t} \) parameter. \( C_0 \) is a 2x2 matrix, the elements of which are zero above the main diagonal; and \( A, B \) are 2x2 matrices. More analytically:

\[
H_t = \begin{pmatrix}
\alpha_{11} & \alpha_{12} \\
\alpha_{21} & \alpha_{22}
\end{pmatrix} + \begin{pmatrix}
a_{11} & a_{12} \\
a_{21} & a_{22}
\end{pmatrix} \varepsilon_{t-1}' \varepsilon_{t-1} + \begin{pmatrix}
\beta_{11} & \beta_{12} \\
\beta_{21} & \beta_{22}
\end{pmatrix} H_{t-1} \begin{pmatrix}
\beta_{11} & \beta_{12} \\
\beta_{21} & \beta_{22}
\end{pmatrix}
\]

The main advantage of the BEKK-GARCH model is that it guarantees by construction that the covariance matrices in the system are positive (Engle and Kroner, 1995). Assuming multivariate General Error Distribution (GED), the maximum likelihood methodology is used to jointly estimate the parameters of the mean and the variance equations. More specifically, in an attempt to identify the possible effects the terrorist incident in question had on FTSE and \( y \) (where \( y=\)DAX or CAC) stock index returns co-movement, we employ the unrestricted BEKK-GARCH (1,1) model including a dummy variable about terror activity in 07/07/2005 in the construction of variances and covariance matrices. This dummy variable takes the value of one for the 10-minute ticks between 07/07/2005 8:50 and 07/07/2005 10:50 (British
summer time, BST) and zero anywhere else. Therefore the functional form of our model is the following:

\[ R_{t,t} = \mu_t + \epsilon_{t,t} \]  

with \( \epsilon_t | \Phi_{t-1} \sim \text{GED}(0, H_t) \) and

\[ H_t = C_0 C_0 + A \epsilon_{t-1} \epsilon_{t-1}' A + B' H_{t-1} B + K \cdot \text{Dum}_t \]

where the K is the coefficient matrix for terror index and the operator “•” is the element by element (Hadamard) product. In that case the model may be written in single equation format as follows:

\[ h_{1,t} = c_{11} + \alpha_{11} \epsilon_{t-1}^2 + 2\alpha_{12} \epsilon_{t-1} \epsilon_{t-1} + \alpha_{21} \epsilon_{t-1}^2 + \beta_{11} h_{1,t-1} + 2\beta_{12} h_{2,t-1} + \beta_{21} h_{22,t-1} + \kappa_{11} \text{Dum}_t \]

\[ h_{2,t} = c_{21} + \alpha_{12} \epsilon_{t-1}^2 + (\alpha_{21} \epsilon_{t-1} + \alpha_{22}) \epsilon_{t-1} \epsilon_{t-1} + \alpha_{22} \epsilon_{t-1}^2 + \beta_{11} h_{1,t-1} + \beta_{12} h_{2,t-1} + \beta_{22} h_{22,t-1} + \kappa_{12} \text{Dum}_t \]

\[ h_{22,t} = c_{22} + \alpha_{12} \epsilon_{t-1}^2 + 2\alpha_{21} \epsilon_{t-1} \epsilon_{t-1} + \alpha_{22} \epsilon_{t-1}^2 + \beta_{12} h_{1,t-1} + 2\beta_{22} h_{2,t-1} + \beta_{22} h_{22,t-1} + \kappa_{22} \text{Dum}_t \]

The error terms in each model represent the effect of news in each model on the different indices. In particular, the terms \( \epsilon_{t-1}^2 \), \( \epsilon_{t-1} \) represent the deviations from the mean attributed to the unanticipated event in each market. The cross values of the error terms \( \epsilon_{t-1} \epsilon_{t-1} \) represent the news in the first and second index in time of period t-1. By \( h_{1,t-1}, h_{2,t-1}, h_{22,t-1} \) we describe the conditional variance for the first stock index (in our case FTSE-100) at time t-1, conditional variance for the second stock index (in our case CAC-40 or

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\( ^3 \) In order to count for the effect induced by the events occurred in 08:50 and 09:50 respectively we have used a dummy taking the value of one from the first bomb explosion lasting one hour and for the second bomb also lasting also one hour.
DAX-30) at time t-1, and the conditional covariance between the first and the second index in our model⁴.

3. Findings and Discussion

Daily data can often conceal a significant part of underlying dynamics of a times series especially during a crisis day in the stock markets. The case of the terrorist attack in London and the reaction of the other two European markets as a result of this event is such a case. Table 1 provides information using daily data for +/- 1 days around the event day. As it can easily be seen, the markets in the event day exhibit negative returns (FTSE -1.37%, CAC – 1.39% and DAX –1.86%). However, as it emerges by the data presented in the last column of Table 1, the difference between the intraday high and low values during the day is appreciably higher for every market compared to the relevant values of the +/- 1 days window. It would appear that studying the microstructure of the data may reveal important information for trading and possible hedging activities.

Figure 1 plotted with the use of tick-by-tick data reveals the magnitude of market agents’ reaction to the event in question that took place between 08:50 and 09:50 in the morning. All three stock markets reacted negatively to the news. Apparently, a considerable amount of selling orders exerted a significant downward pressure in all three cases. The markets begin to recover after 10:50 probably by discounting the short-term effect of the event on the economy but also by recognizing important information about the event⁵.

⁴ For different type of models based on the MGARCH family see for instance Kollias et al. (2011c), Karagianni and Kyrtsou (2011), Karagianni et al. (2010).

⁵ See for instance Kollias et al. 2011b, that compare this attack to the one in Madrid in 2004.
Table 1 Stock Prices +/- one day of the event - Daily data frequency

<table>
<thead>
<tr>
<th>Date</th>
<th>Open</th>
<th>High</th>
<th>Low</th>
<th>Close</th>
<th>Daily Return</th>
<th>High-Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTSE-100 Index</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jul 6, 2005</td>
<td>5,190.10</td>
<td>5,237.60</td>
<td>5,190.10</td>
<td>5,229.60</td>
<td>0.758%</td>
<td>47.50</td>
</tr>
<tr>
<td>Jul 7, 2005</td>
<td>5,229.60</td>
<td>5,229.60</td>
<td>5,022.10</td>
<td>5,158.30</td>
<td>-1.373%</td>
<td>207.50</td>
</tr>
<tr>
<td>Jul 8, 2005</td>
<td>5,158.30</td>
<td>5,232.20</td>
<td>5,158.30</td>
<td>5,232.20</td>
<td>1.422%</td>
<td>73.90</td>
</tr>
<tr>
<td>DAX-30 Index</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jul 6, 2005</td>
<td>4,607.57</td>
<td>4,636.96</td>
<td>4,607.57</td>
<td>4,615.49</td>
<td>0.257%</td>
<td>29.39</td>
</tr>
<tr>
<td>Jul 7, 2005</td>
<td>4,595.23</td>
<td>4,595.23</td>
<td>4,444.94</td>
<td>4,530.18</td>
<td>-1.866%</td>
<td>150.29</td>
</tr>
<tr>
<td>Jul 8, 2005</td>
<td>4,560.43</td>
<td>4,597.97</td>
<td>4,559.57</td>
<td>4,597.97</td>
<td>1.485%</td>
<td>38.40</td>
</tr>
<tr>
<td>CAC-40 Index</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jul 6, 2005</td>
<td>4,272.64</td>
<td>4,292.07</td>
<td>4,264.00</td>
<td>4,279.95</td>
<td>0.638%</td>
<td>28.07</td>
</tr>
<tr>
<td>Jul 7, 2005</td>
<td>4,269.56</td>
<td>4,269.77</td>
<td>4,089.27</td>
<td>4,220.62</td>
<td>-1.396%</td>
<td>180.50</td>
</tr>
<tr>
<td>Jul 8, 2005</td>
<td>4,264.71</td>
<td>4,300.31</td>
<td>4,252.07</td>
<td>4,300.31</td>
<td>1.871%</td>
<td>48.24</td>
</tr>
</tbody>
</table>

Figure 1 Stock Prices the days around and during the event.

Intraday stock market returns are used to conduct our analysis given that their prices are characterized as I(1) processes. Table 2 presents the descriptive statistics for the return series in all three stock markets. In terms of the mean, standard deviation and maximum returns, the three markets present fairly similar characteristics. Skewness and kurtosis measures indicate deviation from normality. The latter is confirmed by the Jarque-Bera test that provides evidence against normally distributed tick-by-tick returns. Therefore preliminary statistical analysis confirms well-known stylized facts of financial markets including significant asymmetry and kurtosis. Hence, the use of
GARCH type models as a tool to take into account non-normal covariations between stock index returns seems to be appropriate.

Table 2 Descriptive Statistics of Intraday data

<table>
<thead>
<tr>
<th></th>
<th>CAC - 40 Index</th>
<th>DAX - 30 Index</th>
<th>FTSE -100 Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.16E-05</td>
<td>1.35E-05</td>
<td>8.09E-06</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.0128</td>
<td>0.0156</td>
<td>0.0101</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.0168</td>
<td>-0.0229</td>
<td>-0.0138</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.0009</td>
<td>0.0011</td>
<td>0.0007</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.9576</td>
<td>-1.9041</td>
<td>-0.7345</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>40.8166</td>
<td>62.1455</td>
<td>40.6416</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>612336.3</td>
<td>1500214</td>
<td>606051.9</td>
</tr>
<tr>
<td>Probability</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
<td>(0.00)***</td>
</tr>
<tr>
<td>Observations</td>
<td>10250</td>
<td>10250</td>
<td>10250</td>
</tr>
</tbody>
</table>

Notes: The sample contains every ten minutes index returns from January 21, 2005 to October 28, 2005. The total number of usable observations is 10250. The values in parenthesis are the actual probability values.

The results for the unrestricted BEKK-GARCH(1,1) model that includes FTSE-100 and CAC-40 index are presented in the second column of Table 3. While the third column of this table, presents the results for the FTSE-100 and DAX-30 indices. The majority of the estimated parameters are statistically significant (the exception being the coefficient c_{22} for the FTSE-CAC pair and the coefficient k_{12} for the FTSE-DAX pair).
### Table 3 BEKK-GARCH estimation results

<table>
<thead>
<tr>
<th></th>
<th>$R_{FTSE}^2$</th>
<th>Coef</th>
<th>T-Stat</th>
<th>Significance</th>
<th>$R_{CAC}^2$</th>
<th>Coef</th>
<th>T-Stat</th>
<th>Significance</th>
<th>$R_{RFTSE}^2$</th>
<th>Coef</th>
<th>T-Stat</th>
<th>Significance</th>
<th>$R_{DAX}^2$</th>
<th>Coef</th>
<th>T-Stat</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_1$</td>
<td>2.06E-05</td>
<td>3.5792</td>
<td>(0.00)**</td>
<td>1.43E-05</td>
<td>2.4995</td>
<td>(0.01)**</td>
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</tr>
<tr>
<td>$\mu_2$</td>
<td>3.53E-05</td>
<td>5.7437</td>
<td>(0.00)**</td>
<td>2.29E-05</td>
<td>3.2235</td>
<td>(0.00)**</td>
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</tr>
<tr>
<td>$\gamma_{11}$</td>
<td>1.38E-04</td>
<td>11.0648</td>
<td>(0.00)**</td>
<td>1.69E-04</td>
<td>14.5381</td>
<td>(0.00)**</td>
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<tr>
<td>$\gamma_{21}$</td>
<td>-2.03E-04</td>
<td>-18.3809</td>
<td>(0.00)**</td>
<td>-1.71E-04</td>
<td>-25.0495</td>
<td>(0.00)**</td>
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<tr>
<td>$\gamma_{22}$</td>
<td>-9.49E-08</td>
<td>-0.0011</td>
<td>(0.99)</td>
<td>9.05E-05</td>
<td>2.4106</td>
<td>(0.01)**</td>
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</tr>
<tr>
<td>$\alpha_{11}$</td>
<td>0.0708</td>
<td>4.5858</td>
<td>(0.00)**</td>
<td>0.0466</td>
<td>3.3165</td>
<td>(0.00)**</td>
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<tr>
<td>$\alpha_{12}$</td>
<td>-0.1859</td>
<td>-9.9818</td>
<td>(0.00)**</td>
<td>-0.3094</td>
<td>-14.6117</td>
<td>(0.00)**</td>
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<tr>
<td>$\alpha_{21}$</td>
<td>0.4181</td>
<td>30.4021</td>
<td>(0.00)**</td>
<td>0.356</td>
<td>35.9818</td>
<td>(0.00)**</td>
<td></td>
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</tr>
<tr>
<td>$\alpha_{22}$</td>
<td>0.6211</td>
<td>38.8304</td>
<td>(0.00)**</td>
<td>0.6613</td>
<td>44.8160</td>
<td>(0.00)**</td>
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<td>$\beta_{11}$</td>
<td>0.9832</td>
<td>106.8976</td>
<td>(0.00)**</td>
<td>0.9622</td>
<td>107.9122</td>
<td>(0.00)**</td>
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<td>$\beta_{12}$</td>
<td>0.2914</td>
<td>20.2541</td>
<td>(0.00)**</td>
<td>0.2865</td>
<td>16.7964</td>
<td>(0.00)**</td>
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<td>$\beta_{21}$</td>
<td>-0.1112</td>
<td>-14.9384</td>
<td>(0.00)**</td>
<td>-0.0851</td>
<td>-15.8730</td>
<td>(0.00)**</td>
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<tr>
<td>$\beta_{22}$</td>
<td>0.6962</td>
<td>71.2779</td>
<td>(0.00)**</td>
<td>0.7365</td>
<td>93.4738</td>
<td>(0.00)**</td>
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<tr>
<td>$\kappa_{11}$</td>
<td>1.96E-03</td>
<td>2.6726</td>
<td>(0.00)**</td>
<td>1.34E-03</td>
<td>2.3346</td>
<td>(0.01)**</td>
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<tr>
<td>$\kappa_{12}$</td>
<td>3.20E-03</td>
<td>3.1997</td>
<td>(0.00)**</td>
<td>1.20E-03</td>
<td>1.1549</td>
<td>(0.24)</td>
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<tr>
<td>$\kappa_{22}$</td>
<td>1.51E-03</td>
<td>3.4415</td>
<td>(0.00)**</td>
<td>1.79E-03</td>
<td>3.6426</td>
<td>(0.00)**</td>
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GED Parameter 0.9268 190.8245 (0.00)** 0.9459 196.4359 (0.00)**
Observations 10250 10250
Log Likelihood 121740.7 120011.7

Notes: ***, **, * indicate statistical significance at 1%, 5% and 10% level.

Note that the volatilities of the CAC and DAX indices are directly affected by the news generated within their own market $\varepsilon^2_{t-1}$ and they are also indirectly affected by news generated from the London market ($\varepsilon^2_{t-1}$, $\varepsilon^2_{2,t-1}$, and $\varepsilon^2_{1,t-1}$). As far as the indirect effects of news by German and French markets on London market are concerned, they are also present but it seems that they are lower in magnitude as it can be deduced from the relevant coefficients in absolute terms ($\alpha_{12} > \alpha_{21}$). Moreover, the volatilities of all the indices’ returns are directly affected by their own past volatilities respectively (the relevant coefficient is 0.96 for the UK market and 0.48, 0.54 for the French and German market respectively). Indirect effects of past volatilities are also present in each case. However, the indirect effects of the London market on
the CAC and DAX volatilities respectively, are higher compared to the indirect effects of the latter on FTSE ($\beta_{22} > \beta_{21}$). Focusing on the covariance equation in the bivariate BEKK-GARCH models, unexpected shocks in London market reduce the covariance between FTSE and CAC or DAX. But unexpected shock in the French and German markets increases their covariance with the London market.

**Figure 2** Conditional Volatilities and Correlation for FTSE-CAC intraday stock returns
On the one hand, the results are uniformed in terms of the effect of the terrorism dummy variable on volatilities. There is evidence of a positive and statistically significant effect (k_{ii} coefficients) on London, French and German market volatilities. Among them, the higher positive coefficient is present in the case of London and this finding is as one would intuitively expect. On the other hand, the direct effect of the terrorist attack on the correlation between the stock markets is not uniform. The correlation is directly, significantly and positively affected in the case of the FTSE - CAC pair (see coefficient k_{12}). While for the FTSE – DAX pair, their correlation seems to not be affected in statistically significant degree. For both cases, indirect effects are present from
the positive and statistically significant effect of the London market volatility on the covariance term (cross term $\beta_{11}\beta_{12}$). Finally, past correlation seems to affect similarly current correlation in every pair of the indices ($\beta_{21}\beta_{12}+\beta_{11}\beta_{12}$). In Figures 2 and 3, the significant positive effect on intraday stock market volatilities during the event day for the FTSE-CAC and the FTSE-DAX pairs of indices$^6$ is clearly visible. Moreover, for the case of FTSE-CAC pair the correlation is significantly increased during the event minutes implying no diversification benefits across these two markets. In contrast, the correlation is not affected in a statistically significant and positive manner for the FTSE-DAX pair of indices.

4. Concluding Remarks

As many studies have shown (inter alia: Fernandez, 2008; Nikkinen et al. 2008; Barros and Gil-Alana, 2009; Ramiah et al. 2010; Drakos, 2010a; Kollias et al. 2011b) terrorist events exert a negative, albeit generally short-lived, impact on stock markets and equity returns. Shocks from terrorist events are also transmitted cross-nationally and affect other financial markets apart from the one of the country that was the venue of the attack (Hon et al. 2004; Mun, 2005; Drakos, 2011, 2010b). The cross-market transmission of the shock caused by a major European terrorist event, namely the bomb attacks of 2005 in London, was the theme of this study using high frequency intraday data. Results reported herein, indicate that the contagion effect, as it is defined by Forbes and Rigobon (2002), is mainly present from the London

$^6$The second column of each graph zooms in on the event day window in order to present in a more clear manner the effect.
to the Paris market. The correlation between FTSE and CAC indices is increased significantly during the minutes of the event (i.e. in the crisis period), implying low benefits from diversification between these two markets. Moreover, there is also a significant positive effect of the London market volatility on the CAC and DAX indices’ volatilities. Finally, over the time period of the event, stock market volatilities are high in all of our three cases, implying suggesting possible gains by intraday trading activity in derivative markets.
References


