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MODELING INTERNATIONAL STOCK PRICE COMOVEMENTS WITH HIGH-FREQUENCY DATA

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This paper studies stock price comovements in two key regions [the United States and Europe, which is represented by three major European developed countries (France, Germany, and the United Kingdom)]. Our paper uses recent high-frequency data (HFD) and investigates price comovements in the context of "normal times" and crisis periods. To this end, we applied a non-Gaussian Asymmetrical Dynamic Conditional Correlation (ADCC)-GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model and the Marginal Expected Shortfall (MES) approach. This choice has three advantages: (i) With the development of high-frequency trading (HFT), it is more appropriate to use HFD to test price linkages for overlapping and nonoverlapping data. (ii) The ADCC-GARCH model captures further asymmetry in price comovements. (iii) The use of the MES enables to measure systemic risk contributions around the distribution tails. Accordingly, we offer two interesting findings. First, while the hypothesis of asymmetrical and time-varying stock return linkages is not rejected, the MES approach indicates that both European and US indices make a considerable contribution to each other's systemic risk, with significant input from Frankfurt to the French and US markets, especially following the collapse of Lehman Brothers. Second, we show that the propagation of systemic risk is higher during the crisis period and overlapping trading hours than during nonoverlapping hours. Thus, the MES test is recommended as an indicator to help monitor market exposure to systemic risk and to gauge expected losses for other markets.

Keywords: Price Comovements, Systemic Risk, HFD, ADCC-GARCH, MES

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1. INTRODUCTION

Systemic risk has been a key ingredient in theories on risk management, asset pricing, and modern finance for a number of years. Further, in the aftermath of the global financial crisis (2008–2009), the debate concerning systemic risk and its measurement was also revived by several financial analysts and economists. They pointed not only to its responsibility and culpability with regard to this crisis, but also to its evaluation errors and the danger and severity of its rapid propagation. Accordingly, traditional financial risk measures have been criticized and systemic risk measurement has again become a topic of intense discussion among economists, bankers, analysts, and policy makers. All of them unanimously agree on the urgency to develop a successful risk management strategy and more accurate risk assessment.[1]

Consequently, an ongoing research program has been developed, focusing on at least two different lines of study. On the one hand, various robust financial asset volatility risk measurements have been introduced to improve risk management and measure, including the use of recent financial econometric methods [Dettling and Bühlmann (2002), Bollerslev and Zahang (2003), Härdle et al. (2008), Ait-Sahalia and Yu (2009), Dobrev and Szerszen, (2010), Anderson et al. (2011)]. On the other hand, a new focus on the measurement of stock market linkages—yielding different systemic risk measures—has been noted in the recent literature, and is designed to better model market interactions [Conditional Value-at-Risk, noted CoVaR, by Adrian and Brunnemeir (2016), Multi-CoVaR by Cao (2012), Marginal Expected Shortfall (MES) by Acharya et al. (2010), Brownlees and Engle (2012), etc.]. By definition, let us recall that the VaR measures for a firm i the highest loss that it can expect, while the CoVaR measures the Value-at-Risk (VaR) of a given financial system with regard to a specific event that characterizes a given institution. The ΔCoVaR captures the contribution of a given institution to systemic risk and is measured as the difference between its CoVaR when the institution is in a stress situation and its CoVaR in a normal situation. Finally, the MES that measures the expected loss of a given institution when the financial system falls below a given threshold.[2]

Our paper examines this second line of research, supporting substantial gains in the modeling of stock price comovements by using high-frequency data (noted HFD hereafter) and recent systemic risk measures. Investigation of intraday price linkages is crucial to improve our understanding of shock transmission and systemic risk diffusion from one market to another.

Obviously, stock market linkages and systemic risk are not new issues, and have been the focus of several empirical studies in different forms (contagion, financial integration) but often through low-frequency data. With the expansion of high-frequency trading (noted HFT hereafter) across markets,[3] it becomes interesting to study price comovements more parsimoniously with HFD given the nature of HFT.[4] Indeed, HFT improves market efficiency [Hendershott and Riordan (2009)] and liquidity [Hendershott et al. (2011)], and implies positive externalities for traditional traders. But HDT can also damage financial markets since it can cause higher volatility, information asymmetry, adverse selection, worsened liquidity, and an increase in systematic risk across markets.

In particular, HFT is a source of systemic events (i.e., the Flash Crash in the United States on May 6, 2010, when large indices lost 5% in 30 minutes), and can transmit shocks across markets through at least two mechanisms. First, HF traders might stop the liquidity supply and induce illiquidity spread across markets. Second, HF traders use cross-market arbitrages and adopt similar behaviors and strategies as they exploit trading opportunities in microseconds. They can thus accelerate the markets' interdependency and correlations, making markets more fragile [Debrev and Szerszen (2010)]. It is also widely acknowledged that market fragmentation leads to an increase in HFT, creates cross-sectional correlations, and stimulates price comovements and therefore financial risk [(Forbes and Rigobon (2002)]. For all these reasons, studying intraday price comovements and intraday systemic risk is highly recommended, and our paper focuses on and contributes to this specific field.

From an econometric perspective, unlike previous related studies that often rely on the modeling of unconditional price comovements with standard parametric time-series techniques, we applied two recent methodologies to investigate HF stock prices and thus develop an analysis that paves the way for new lines of research, with several advantages. First, the application of an Asymmetrical Dynamic Conditional Correlation (ADCC)-GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model captures conditional correlations and variance for stock return distributions that are robust to further asymmetry and heteroscedasticity in the data. Second, we use a nonparametric approach based on the MES that measures the tail-event linkages between financial assets, while focusing on the behavior of tail distribution to measure the impact of a given high-intensity shock affecting one market via another market. Interestingly, while the first approach focuses on the whole distribution, the MES captures comovements around the quantiles, which is more appropriate when checking for extreme market risk.

Adopting an empirical approach, our study focuses on an original sample including two key regions [the United States and Europe, which is represented by three major European developed countries (France, Germany, and the United Kingdom)] with implicit reference to three leading international currencies. While the inclusion of the US market is of particular interest as the latter was at the center of the subprime crisis and the global financial crisis (2008–2009), the choice of European markets is explained by the fact that they were strongly affected by these two crises as well as by the European Public Debt crisis in 2010. We use a recent data sample including HFD (5-minute returns) to cover two subsamples: July 2007–March 2009 and January 2014–September 2015. While the first sample focuses on intraday price comovements and intraday systemic risk across leading international equity markets during the crisis period, the second sample acts as a benchmark period that enables us to investigate price comovements and systemic risk transmission in normal times. Interestingly, when we apply the MES (that provides a measure of sensitivity or resilience) in normal periods (sample 2), we test whether the MSE test could provide an indicator of actual or future losses [Acharya et al. (2010)].

Thus, the first contribution of this study is linked to the investigation of intraday price comovements for four major stock markets during normal and crisis periods. The second contribution comes from the nonparametric modeling (MES) of systemic risk transmission from one market to another at different periods of the trading day, especially during overlapping and nonoverlapping hours. The MES is better adapted than the usual parametric method as it captures comovements around quantiles of the distribution and movements associated with extreme risk and events.

Overall, our findings offer three interesting results. First, the ADCC-GARCH approach shows significant time-varying stock return linkages and points to further asymmetry in these linkages, indicating that markets are closely connected and that their reaction to negative shocks differs from their reaction to positive ones. Second, the MES approach suggests that both European and US indexes significantly contribute to each other's systemic risk, with strong input from Frankfurt to the French and US markets, especially following the collapse of Lehman Brothers. Third, both analyses indicate that stock return linkages and contributions to systemic risk significantly increase during overlapping trading hours (OTH) when the US market opens, and during the crisis period. This suggests that the probability of systemic risk transmission is higher when all of the markets are open.

The remainder of the paper is organized as follows. Section 2 briefly summarizes a related literature survey. Section 3 presents the econometric methodology. The empirical results are discussed in Section 4. Finally, Section 5 concludes.

2. LITERATURE

The study of comovements between international stock markets has received a great deal of interest in the quantitative finance literature as it is an important factor in helping investors to optimize their investment and diversification strategies. This has led to an ongoing literature[5] that includes various studies on stock return linkages and volatility spillovers, based on diverse econometric methodologies that can be split into three different approaches. A first approach consists of examining the unconditional correlation between international stock market returns [Jaffe and Westerfield (1985), Calvo and Reinhart (1996), Forbes and Rigobon (2002), Chiang et al. (2007)], but it is not the most reliable given the nonnormality of such returns. A second approach uses different versions of international capital markets to test the hypothesis of market integration [see Bekaert and Harvey (1995)]. Linear and nonlinear cointegration tests are central to the third approach and involve identifying further long-run relationships between stock prices [Girardin and Liu (2007), Jawadi et al. (2009), Arouri et al. (2012), Chlibi et al. (2015), Chlibi et al. (2016), etc.]. Overall, these studies have pointed to an increase in price comovements over the last few decades, but the conclusions in terms of stock market integration and/or contagion phenomena vary with regard to the markets under consideration and their shared level of fundamentals. The following three major empirical results may be retained, however:

(i) Developed stock markets show higher integration than emerging stock markets, implying that they depend on both local and global risk factors.
(ii) Financial integration across emerging markets has increased in recent years due to the different financial reforms, liberalization, integration, and deregulation. In addition, the increase in market integration indicates an increase in cross-market linkages and therefore systemic risk.
(iii) Stock price comovements seem to exhibit asymmetry, nonlinearity, and threshold effects.

As for the literature related to volatility spillover, the family of ARCH models has been widely applied to characterize volatility dynamics in financial markets, since ARCH models can reproduce the volatility persistence effect (clustering) and capture the conditional heteroscedasticity that informs most stock data. Furthermore, extensions of ARCH models, including the Exponential-GARCH and Threshold-ARCH models, justify the predominance of such models since they account for the well-known asymmetric effect, i.e., negative shocks have a greater impact on conditional volatility than positive shocks, and enable structural breaks and switching regimes in volatility dynamics, respectively.

For a nonexhaustive list, we summarize this body of volatility spillover literature below. Hamao et al. (1990) considered a univariate GARCH model to investigate the interdependence between three major international stock markets (London, New York, and Tokyo) around the time of the October 1987 crash. Their study highlighted price volatility spillover from New York to Tokyo, London to Tokyo, and New York to London. Koutmos and Booth (1995) used a multivariate EGARCH model, which takes the asymmetric response of volatility to external events into account. They distinguished between the impact of good news (market advances) and bad news (market declines). The study revealed that volatility spillover is far more pronounced when the news transmitted from one market to another is bad. Koutmos (1996) confirmed the above result when studying volatility spillover among the four major European stock markets (United Kingdom, France, Germany, and Italy). By using a bivariate GARCH model, Ng (2000) found a significant volatility spillover effect from Japan and the United States to six Pacific-Basin equity markets. Baele (2005) examined volatility spillover from the aggregate European and US market to 13 local European equity markets. The author found that the intensity of both the European and the US shock spillover increased substantially during the 1980s and 1990s. Nam et al. (2008) focused on price and volatility spillover from the US market to five Pacific-Basin markets: Hong Kong, Singapore, South Korea, Malaysia, and Taiwan. The authors compared the spillover effects between the pre and postcrisis periods and showed that the impact of US shocks on the volatility of Asian markets

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decreased significantly after the 1997 financial crisis. By using a bivariate vector autoregression-generalized autoregressive conditional heteroskedasticity model, Lee (2009) found evidence of volatility spillover between six Asian stock markets (India, Hong Kong, South Korea, Japan, Singapore, and Taiwan). Overall, significant dependency on the US market seems to be confirmed by a number of empirical studies. Furthermore, the hypothesis of price comovement increases for major stock markets is not rejected but appears to vary according to the markets and periods considered, suggesting more evidence of time-varying stock return and volatility linkages.[6]

In order to get a better grasp of stock market comovements and systemic risk, some recent studies have extended the topic by examining intradaily data instead of daily or weekly information. This choice is justified by the development of new information and communication technologies, access to information in real time and the development of HFT. Among this body of studies, Susmel and Engle (1994) tested hourly volatility spillover between New York and London, but the authors did not find strong volatility spillover between the two markets. Jeong et al. (1999) used 5-minute returns to study volatility spillover between the United States, United Kingdom, and Canada during their OTH (9:30–11:30 a.m., New York time) and showed that information contained in price volatility surprises in a domestic market is subsequently transmitted to foreign markets. Moreover, they detected some persistence in the impact of foreign volatility shocks on the conditional variance of the domestic market. Chang et al. (2011) examined intraday returns spillover between technology stocks quoted on the NYSE, AMEX, and NASDAQ. The authors found that spillover effects occur within half an hour and two hours later, and tend to follow an M-shaped intraday pattern. Overall, these studies refine the analysis of systemic risk and stock market comovements thanks to the use of HFD.[7] However, the techniques employed are not robust to asymmetry and have so far failed to significantly distinguish between negative and positive shocks or high- and low-intensity shocks. In addition, the effect of extreme market risk on another market cannot be appropriately reproduced with the linear techniques employed in these prior studies.

To fill this gap, our study adopts two techniques (ADCC-GARCH and MES) and applies them to recent HFD for the United States and three major European stock markets (France, Germany, and the United Kingdom) to capture their interactions in real time. Accordingly, the present paper contributes to the literature through the investigation of systemic risk propagation by using nonparametric interdependence tests applied to four international equity markets during overlapping and nonoverlapping hours. To our knowledge, this is the first study to test stock price comovements and systemic risk with HFD by using nonparametric approaches that simultaneously search for further asymmetry and spillover effects between extreme market risks. The MES approach is useful to capture different forms of price linkages and improve systemic risk modeling, since it enables us to measure and time the contribution of a given market to the systemic risk of another market for each quantile.

3. ECONOMETRIC METHODOLOGY

This section briefly presents the econometric methodology: (i) the ADCC-GARCH model and (ii) the MES methodology.

3.1. The ADCC-GARCH Model

The ARCH effect that characterizes financial data is appropriately reproduced by the class of Autoregressive Conditional Heteroscedasticity models, including the ARCH model [Engle (1982)] and the GARCH model [Bollerslev (1986)] and their recent extensions (EGARCH, TARCH, PARCH, GJR-GARCH, etc.). These specifications are used to model daily as well as intraday 5-minute conditional volatility [Kalev et al. (2004), Bauwens et al. (2005), Baur and Jung (2006), Louhichi (2011), Jawadi et al. (2015a), etc.]. However, the basic GARCH model considers that conditional correlations are constant over time, although this hypothesis is restrictive in practice, as observed volatilities appear to move more or less closely together over time. In order to take these time-varying correlations into account, several multivariate GARCH specifications have been developed.[8] First, Engle and Kroner (1995) proposed a general multivariate GARCH model: the BEKK-GARCH. The latter is sufficiently general to include all positive definite diagonal representations and nearly all positive definite vector representations. However, the main drawback of the BEKK-GARCH model is the presence of a large number of parameters, which can increase rapidly with the size of the model. Second, Engle and Sheppard (2001) proposed the dynamic conditional correlation-GARCH model, called the DCC-GARCH model. Cappiello et al. (2006) then extended the DCC-GARCH model to allow for asymmetry in modeling time-varying conditional correlations, and introduced the ADCC-GARCH model. This new class of dynamic correlation model is much simpler in that it requires a two-step algorithm to estimate the model parameters. In the first step, the conditional variance is separately estimated for each time series via a univariate GARCH model. The second step consists of generalizing Bollerslev's Constant Conditional Correlation (CCC) to capture further dynamic correlations. The parameters for the conditional correlation are estimated taking the parameters from the first step into account. Interestingly, the ADCC-GARCH provides an appropriate framework to study price comovements and investigate systemic risk, while allowing for price comovements to be asymmetrical since the effects of positive shocks can differ from those of negative shocks.

Formally, we note r_t as a vector of stock returns and specify its dynamics as follows:

$$r_t = \mu + \varepsilon_t, \tag{1}$$

where r_t denotes the returns' vector, μ denotes the vector of conditional returns, and ε_t is the vector of mean-corrected returns of n assets at time t.

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We specify ε_t as follows:

$$\varepsilon_t = H_t^{\frac{1}{2}} z_t, \tag{2}$$

where H_t is a matrix of conditional variances of ε_t, $z_t \rightsquigarrow$ i.i.d. $(0, I)$, and I denotes the identity matrix.

The matrix H_t is defined as follows:

$$H_t = D_t\ R_t\ D_t, \tag{3}$$

where D_t is the diagonal matrix of time-varying standard deviations and R_t is the matrix of conditional correlation of the standardized residuals.

The matrix D_t is based on time-varying standard variations from a univariate GARCH model and corresponds to the following:

$$D_t = \begin{bmatrix} \sigma_{1,t} & 0 & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & 0 & \cdots & 0 \\ 0 & 0 & \sigma_{3,t} & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}. \tag{4}$$

The diagonal elements of D_t are obtained from the following GARCH (p, q) specification[9]:

$$\sigma_t^2 = k + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + v_t, \tag{5}$$

where k is a constant, $v_t \rightsquigarrow N(0, \sigma_v^2)$, α_i and β_j are the ARCH and GARCH parameters, respectively, and p and q are the max-lag numbers.

As for the matrix R_t, it reproduces conditional correlation of the standardized residuals $[\ \epsilon_t = D_t^{-1} r_t \longrightarrow N\ (0, R_t)]$ and it corresponds to the following:

$$R_t = \begin{bmatrix} 1 & \varphi_{12,t} & \varphi_{13,t} & \cdots & \varphi_{1n,t} \\ \varphi_{21,t} & 1 & \varphi_{23,t} & \cdots & \varphi_{2n,t} \\ \varphi_{31,t} & 0 & 1 & & \vdots \\ \vdots & \vdots & & \ddots & \\ \varphi_{n1,t} & \varphi_{n2,t} & \varphi_{n3,t} & \cdots & 1 \end{bmatrix}. \tag{6}$$

Thus, in practice, a GARCH structure is used to model the correlation dynamics. This means that an ADCC process of order (M, N) can be described as follows:

$$R_t = \left(Q_t^*\right)^{-1} Q_t \left(Q_t^*\right)^{-1}, \tag{7}$$

$$Q_t = (1 - a - b)\ \overline{Q} - c\overline{T} + a\ (\epsilon_{t-1}\epsilon_{t-1}) + b\ Q_{t-1} + c\ \left(e_{t-1}e_{t-1}'\right),$$

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where $\overline{Q} = E(\epsilon_t \epsilon_t')$ denotes the unconditional and time-invariant variance–covariance matrices, a and b measure the effects of shocks and dynamic correlations, respectively, and c captures the asymmetric effect, Q^* is a diagonal matrix containing the square root of the diagonal elements of Q_t, $e_t = I(\epsilon_t < 0) \circ \epsilon_t$ ($\circ$ denotes the Hadmard product elementwise matrix multiplication), and $\overline{T} = E(e_t e_t')$.

In order to ensure the stationarity and positivity for Q_t, we need to check the following required conditions:

$$a + b + dc < 1,$$

where d denotes the maximum eigenvalue of $\overline{Q}^{-\frac{1}{2}} \overline{T} \overline{Q}^{-\frac{1}{2}}$.

As for Q_t^*, we specify it as

$$Q_t^* = \begin{bmatrix} \sqrt{\varphi_{11,t}} & 0 & 0 & \cdots & 0 \\ 0 & \sqrt{\varphi_{22,t}} & & \cdots & 0 \\ 0 & 0 & \sqrt{\varphi_{33,t}} & 0 & 0 \\ \vdots & \vdots & 0 & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sqrt{\varphi_{nm,t}} \end{bmatrix}. \tag{8}$$

The estimation of the ADCC-GARCH model is performed by using a two-step procedure that allows for decreases in the complexity of the estimation process. In particular, Engle et al. (2008) introduced a composite likelihood approach to covariance modeling, thereby making use of these plausible methods for large-scale applications. Interestingly, this approach resolves the problem of bias in the two-step quasilikelihood estimators. Composite likelihood is thus maximized to determine the parameters of the ADCC-GARCH. The advantage of this model is that it uses a dynamic multivariate distribution on top of the dynamic marginal distributions. It can be viewed as a simple type of dynamic copula approach without modeling distributions specifically.

3.2. The Margin Expected Shortfall Approach

By using the ADCC-GARCH model, it is possible to capture further price dependency through the dynamic correlation measure that is based on mean changes in price. However, this model cannot capture price comovements induced by changes in the tail distribution, a major source of systemic risk. In order to take extreme price movements into account, quantile regressions are required, as extreme price variations affect quantiles far more than the mean or median distribution in periods of stress.[10]

The ES and/or MES approaches have been applied to measure this type of comovement in several recent studies [Inui and Kijima (2005), Idier et al. (2014)]. They are particularly suitable to assess the measurement of systemic risk exposure.

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The main advantage of the former is that it is not affected by the problem of subadditivity as is the VaR [Artzner et al. (1999)].

In this paper, we apply the MES approach developed by Acharya et al. (2010) to investigate the hypothesis of intraday systemic risk transmission between international stock indexes. This procedure aims at measuring further dependence between intradaily extreme price variations, while identifying the markets that contribute the most to systemic risk across time on other markets. It is worth recalling that the MES methodology is basically applied to compute the risk contribution of an individual asset relative to the whole portfolio. However, the MES is defined mathematically on the basis of joint distribution, so it can also be used to estimate the risk contribution of an index relative to another index.

Formally, Acharya et al. (2010) define MES as the marginal contribution of a firm J to the expected shortfall of the financial system. Thus, the MES for firm J is the expected value of the stock return R_J conditional on the market portfolio return R_i being at or below the sample p-percent quantile. Let C be a constant that corresponds to the level of market "tail risk," we define the MES as follows:

$$\text{MES}(R_J, p) = E\left(R_j \,|R_i < \text{VaR}\,(R_i, p) = C\right). \tag{9}$$

The higher the MES of an asset, the greater its contribution to the market decline and to systemic risk.[11]

This approach consists of a multistage estimation. In the first step, GARCH models are used to produce conditional volatilities and standardized residuals. In the second step, the ADCC specification allows us to determine the conditional asymmetric correlation. Next, the tail expectation is estimated by a nonparametric kernel estimation approach proposed by Scaillet (2005), who used the Nadaraya–Watson (NW) type double kernel estimator of conditional density. This approach has the advantage of not requiring a hypothesis regarding stock return distribution. Brownless and Engle's (2010) approach also provides smooth estimates of the MES, suggesting that the dynamic MES estimate is not oversensitive to small changes in the threshold level of systemic loss. Also, following Scaillet (2005), we use the Gaussian Kernel function and the bandwidth $h = T^{-\frac{1}{5}}$.

If $r_{j,t}$ and $r_{i,t}$, respectively, define the returns of two market indices, then

$$\begin{aligned} r_{j,t} &= \sigma_{j,t}\varepsilon_{j,t}, \\ r_{i,t} &= \sigma_{i,t}\varepsilon_{i,t}, \\ r_{i,t} &= \sigma_{i,t}\rho_{i,t}\varepsilon_{j,t} + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2\zeta_{i,t}}, \\ (\varepsilon_{j,t}&, \zeta_{i,t}) \to F, \end{aligned} \tag{10}$$

where $\sigma_{j,t}$, $\sigma_{i,t}$, and $\rho_{i,t}$ are, respectively, the volatilities of the market indices j and i and the conditional correlation between the two market indices. The disturbances $\varepsilon_{j,t}$ and $\zeta_{i,t}$ are assumed to be independent and identically distributed.

The joint distribution F allows for the random variables to be uncorrelated but not independent.

4. EMPIRICAL ANALYSIS

4.1. Preliminary Analysis

Our study investigates intradaily price linkages between the US market and three major European stock markets (Frankfurt, London, and Paris). To do this, we used the tick prices of leading stock market indices: SP&500, DAX30, FTSE100, and CAC40. Data were obtained from the Bloomberg database and covers two subperiods: the crisis period from July 2007 to March 2009 and a recent benchmark period from January 2014 to September 2015. As in previous related studies, we relied on 5-minute stock returns. In view of our sample, the use of HFD allows us to investigate short-term linkages between these major international equity markets at different periods of the trading day for OTH and nonoverlapping trading hours (NOTH). During our period of study, the CAC40, the DAX30, and the FTSE100 were continuously computed from 8:00 to 16:30 GMT. However, trading in the US market starts at 14:30 and ends at 21:00 GMT. This means that the US market opens during European market trading hours and continues for more than four trading hours after the European markets have closed. Accordingly, the difference in trading hours helps us to conduct a more precise study by separating overlapping and nonoverlapping periods, with our sample broken down into overlapping and nonoverlapping hours.

Descriptive statistics. Before moving on to the empirical analysis, we investigated the statistical properties of the data during nonoverlapping (Tables 1 and 2) and overlapping (Tables 3 and 4) trading hours and noted several factors. First, the return in mean for both samples differs significantly, highlighting the impact of the opening of the US market. Second, stock return volatilities seem to vary per trading hour and to increase during OTH, suggesting that the opening of the US market and the arrival of news from this market may be a source of volatility increase and therefore systemic risk for European markets. Third, skewness is often negative and statistically significant during overlapping and nonoverlapping hours, pointing to further evidence of left asymmetrical distribution. Fourth, leptokurtic excess during OTH and NOTH suggests that distribution tails are higher than those of a normal distribution. Finally, normality is statistically rejected for all series in both samples.

Unconditional correlation matrix. Next, we checked the linkages between stock returns, again for NOTH (Tables 5 and 6) and OTH (Tables 7 and 8) while computing the unconditional correlation matrix.

Overall, we noted positive and significant unconditional correlations between the stock markets under consideration, with a high correlation for the Paris–Frankfurt pair for all periods, apart from the OTH during the crisis period, where we

TABLE 1. Descriptive statistics for NOTH during the benchmark period

	RCAC	RUK	RDAX
Min	−0.018	−0.010	−0.021
Max	0.012	0.008	0.012
Mean	−1.4575E−06	−7.3341E−06	−3.5013E−06
STD	9.1312E−04	6.2211E−04	9.4104E−04
Median	2.2829E−06	−4.5712E−06	0
Kurtosis	23.256	16.719	20.470
Skewness	0.147	−0.488	−0.626
JB test	5.765E+05	2.647E+04	4.294E+05

Note: RCAC, RUK, and RDAX denote French, British, and German stock returns. STD and JB denote standard deviation and Jarque Bera tests, respectively. NOTH refers to nonoverlapping trading hours.

TABLE 2. Descriptive statistics for NOTH during the crisis period

	RCAC	RUK	RDAX
Min	−0.029	−0.089	−0.028
Max	0.033	0.046	0.031
Mean	−1.6911E−06	−8.7675 E−06	−1.1281E−06
STD	0.0016	0.0016	0.0016
Median	−6.8811E−06	0	−1.2842E−06
Kurtosis	24.886	348.468	30.554
Skewness	−0.637	−3.795	0.238
JB test	6.7215E+05	1.6752E+04	1.0655E+05

note that the highest correlation is between Paris and London, suggesting further evidence of strong intradaily price comovements. Furthermore, we noted that the opening of the US markets stimulates these linkages and increases propagation of systemic risk. The US market seems to be linked more strongly to Frankfurt than to London or Paris. These findings are in line with those of Ben Ameur et al. (2013) and Jawadi et al. (2015a). In comparison with the crisis period, the level of unconditional correlation is highest during noncrisis periods.

While these findings indicate further evidence of dependence between the stock markets under consideration, we need to apply more developed tests to check the hypothesis of intraday systemic risk and intraday comovements between these markets.

4.2. Empirical Analysis

The ADCC-GARCH analysis. First, we applied the ADCC-GJR-GARCH model by using the Composite Likelihood approach developed by Engel et al.

Table 3. Descriptive statistics for OTH during the benchmark period

	RCAC	RUK	RDAX	RSP
Min	−0.0079	−0.0057	−0.0102	−0.0098
Max	0.0113	0.0095	0.0112	0.0141
Mean	−4.4465E−6	−5.3278E−7	−3.9831E−6	−6.0553E−6
STD	0.0011	7.3876E−4	0.0011	8.0503E−4
Median	1.5772E−5	9.9742E−6	1.7574E−4	9.6950E−06
Kurtosis	9.7761	12.3602	9.7907	25.4010
Skewness	0.0524	0.0845	−0.1222	0.5584
JB test	1.7977E+4	3.4304E+4	1.8073E+4	1.9690E+5

Table 4. Descriptive statistics for OTH during the crisis period

	RCAC	RUK	RDAX	RSP
Min	−0.0187	−0.0130	−0.0235	−0.0183
Max	0.0212	0.0181	0.0188	0.0367
Mean	−2.3301E−5	−1.6643E−5	−1.4466E−5	−3.8090E−05
STD	0.0021	0.0019	0.0021	0.0021
Median	−2.8906E−05	−1.6500E−5	−1.1918E−5	−4.3364E−05
Kurtosis	9.3923	8.9849	10.8008	20.0580
Skewness	−0.0780	0.1497	−0.2104	0.6268
JB test	1.5765E+4	1.3846E+4	2.3532E+4	1.1280E+5

Note: RSP denotes the US stock return. OTH refers to overlapping trading hours.

Table 5. Unconditional correlation matrix for NOTH during the benchmark period

	RCAC	RUK	RDAX
RCAC	1.000	0.777	0.892
RUK		1.000	0.735
RDAX			1.000

(2008). According to the information criteria, we retained an ADCC-GJR-GARCH (1,1) specification. Thus, the first step consisted of modeling the stock-return regression according to equation (1). Next, we recuperated its estimated residuals as in Engle and Shepard (2006) and used them to evaluate the GJR-GARCH (1,1) model parameters [equation (11)]. We then computed the parameters a, b, and c of the ADCC-GJR-GARCH (1,1) model with regard to equation (7) under the

Table 6. Unconditional correlation matrix for NOTH during the crisis period

	RCAC	RUK	RDAX
RCAC	1.000	0.759	0.803
RUK		1.000	0.679
RDAX			1.000

Table 7. Unconditional correlation matrix for OTH during the benchmark period

	RCAC	RUK	RDAX	RSP
RCAC	1.000	0.821	0.917	0.725
RUK		1.000	0.794	0.748
RDAX			1.000	0.738
RSP				1.000

Table 8. Unconditional correlation matrix for OTH during the crisis period

	RCAC	RUK	RDAX	RSP
RCAC	1.000	0.863	0.834	0.704
RUK		1.000	0.802	0.706
RDAX			1.000	0.707
RSP				1.000

student distribution hypothesis.

$$\sigma_t^2 = k + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma I_{t-1} \upsilon_{t-1}^2, \tag{11}$$

where $I_{t-1} = \begin{cases} 1 & \text{if } \upsilon_{t-1} \prec 0 \\ 0 & \text{if } \upsilon_{t-1} \succeq 0 \end{cases}$ and γ is the asymmetry parameter.

In practice, we computed this relationship for two different trading hours. Tables 9 and 10 report the results for the European markets only, covering the interval 8:00–14:30 GMT. Accordingly, we note that ARCH and GARCH effects show the appropriate signs and are statistically significant, presenting the required GARCH model conditions for the three European couples under consideration. The asymmetry parameter γ is also statistically significant for all the markets, but only for the Germany market in the OTH crisis period from July 2007 to March 2009. Overall, this suggests stationarity and stability of the estimated GARCH model, and confirms the choice of the GJR-GARCH specification, also indicating that volatilities exhibit significant clustering effects. Interestingly, for the OTH

Table 9. ADCC-GARCH estimation for NOTH during the benchmark period

		C	K	β_1	α_1	γ	LLH
CAC40	GJR	−8.02E–07	1.14E–08	0.880473	0.087595	0.053053	194416.6
		(−0.2407)	(13.1921)	(227.2423)	(18.4140)	(8.1195)	
DAX30	GJR	6.15E–07	9.77E–09	0.8871	0.0873	0.0551	193230.2
		(0.1838)	(12.1004)	(248.9212)	(17.92149)	(8.275304)	
FTSE100	GJR	−1.34E–06	7.40E–09	0.8637	0.1116	0.0297	206499.1
		(−0.5669)	(13.9405)	(195.5115)	(19.5541)	(4.1254)	

		CAC-UK	CAC-DAX	UK-DAX
a	Coefficient	0.0296	0.0269	0.0272
	t-statistics	(12.7108)	(12.5429)	(12.1099)
b	Coefficient	0.9458	0.9494	0.9541
	t-statistics	(207.0033)	(232.3447)	(238.8954)
c	Coefficient	0.0002	0.0006	0.0009
	t-statistics	(1.2209)	(4.1110)	(3.1225)
Log likelihood		415106.7	412142.5	411867.7

period from January 2014 to September 2015, as for the ADCC specification parameters, the parameter c is positive and significant, confirming the asymmetry inherent to European stock data. In addition, the values of a and b confirm the suitability of ADCC-GARCH to specify European stock return comovements, and point to significant dynamic and time-varying correlations. This suggests further evidence of time-varying systemic risk between these markets, while the asymmetric character indicates excess sensitivity to a negative shock rather than to a positive one. For NOTH, the parameter c, which allows us to take the asymmetric effect into account, is not significant for any of the market pairs, while it becomes significant in crisis periods for the CAC-UK and CAC-DAX pairs, suggesting that asymmetry is more significant during turbulent times.

Table 11 reports the results for OTH, when all markets are simultaneously open.

Accordingly, while ARCH and GARCH compounds still show the expected signs and point to the stability and stationarity of the GARCH process, the asymmetric effect depends on the OTH or NOTH period, and the crisis or benchmark period. For the OTH benchmark period from January 2014 to September 2015 (Table 12), the parameter c is significant for all the markets pairs, while it becomes significant only for the pairs that include the US market during the crisis period from July 2007 to March 2009. This suggests that during the crisis period, information from the US market is treated differently, and its effect varies with its sign and size.

TABLE 10. ADCC-GARCH estimation for NOTH during the crisis period

		C	K	β_1	α_1	γ	LLH
CAC40	GJR	−4.94E–06	7.02E–09	0.923380	0.067254	0.024529	179618.9
		(−1.0094)	(8.3069)	(357.3342)	(17.8408)	(5.0394)	
DAX30	GJR	3.62E–06	5.48E–09	0.9246	0.0703	0.0180	182248.3
		(0.8374)	(8.2763)	(368.0805)	(18.24831)	(3.7501)	
FTSE100	GJR	−1.54E–06	1.45E–08	0.895950	0.084560	0.040613	180747.2
		(−0.3185)	(11.5240)	(274.6111)	(18.8578)	(6.7779)	

		CAC-UK	CAC-DAX	UK-DAX
a	Coefficient	0.0222	0.0163	0.0201
	t-statistics	(13.0460)	(8.9337)	(9.1135)
b	Coefficient	0.9594	0.9771	0.9549
	t-statistics	(284.0662)	(322.4510)	(166.6741)
c	Coefficient	−0.0001	−0.0006	−0.0001
	t-statistics	(−0.9481)	(−4.0005)	(−0.6342)
Log likelihood		378399.8	379843.4	376386.3

Furthermore, comparison of the results from the two samples indicates that volatility drivers increase during the overlapping hours, confirming our preliminary analysis. This again points to evidence of more significant volatility clustering effects after the US market opens, in line with Ben Ameur et al. (2013) and Jawadi et al. (2015b). It also indicates time variations in conditional volatilities and correlations.

To check this result, we also computed the conditional correlation between stock returns during NOTH (Figure 1) and overlapping hours (Figure 2). Accordingly, our analysis confirmed the high level of correlation between European stock returns for the first sample, particularly for the Paris–Frankfurt pair, suggesting strong integration between these markets. The time-variation character associated with conditional correlation is also confirmed, indicating that the comovement process is continuous and evolves over time. As for Figure 2, a significant conditional and time-varying correlation between the US market and the three European markets may also be noted, confirming our previous analysis. Interestingly, while these findings point to fewer diversification benefits across these markets, the high level of comovement indicates that the probability of systemic crisis is not insignificant when a given market is going through a period of stress.

Figures 1–4 show the conditional correlation for each market index. We calculated the conditional correlation during nonoverlapping trading hours and overlapping trading hours for the crisis period from July 2007 to March 2009 and for the benchmark period from January 2014 to September 2015.

TABLE 11. ADCC-GARCH estimation for OTH during the crisis period

		C	K	β_1	α_1	γ	LLH
CAC40	GJR	−9.65E–06	6.97E–09	0.947864	0.042763	0.018670	46266.28
		(−0.6974)	(3.3322)	(235.6588)	(8.2250)	(2.9613)	
DAX30	GJR	1.00E–05	3.35E–09	0.947537	0.050892	0.006761	47070.97
		(0.8524)	(2.5831)	(247.1614)	(9.2426)	(1.0345)	
FTSE100	GJR	−5.46E–06	7.78E–09	0.950095	0.038837	0.018926	46936.44
		(−0.4078)	(3.6870)	(231.7352)	(7.8777)	(3.2834)	
SP500	GJR	−1.98E–05	5.67E–09	0.9507	0.0350	0.0281	46801.58
		(−1.5634)	(3.4865)	(255.6320)	(7.5950)	(4.3611)	

		CAC-UK	CAC-DAX	CAC-SP	UK-DAX	UK-SP	DAX-SP
a	Coefficient	0.0165	0.0198	0.0399	0.0165	0.0406	0.0394
	t-statistics	(5.2516)	(6.0301)	(8.8553)	(5.2516)	(9.7552)	(8.9679)
b	Coefficient	0.9761	0.9740	0.9516	0.9761	0.9481	0.9527
	t-statistics	(223.4628)	(222.5876)	(176.8258)	(223.4628)	(182.8965)	(181.0651)
c	Coefficient	0.0005	−6.98E–05	−0.0005	0.0005	0.0001	−0.0015
	t-statistics	(1.7932)	(−0.1636)	(−0.5658)	(1.7932)	(0.1972)	(−1.6678)
Log likelihood		99187.59	98752.36	97376.84	99187.59	97782.31	98260.36

TABLE 12. ADCC-GARCH estimation for OTH during the benchmark period

		C	K	β_1	α_1	γ	LLH
CAC40	GJR	1.80E–05	1.53E–08	0.9009	0.0663	0.04225	52300.21
		(2.1800)	(6.6813)	(130.8302)	(8.0449)	(4.0961)	
DAX30	GJR	2.01E–05	1.35E–08	0.910216	0.066600	0.034642	51775.83
		(2.3565)	(5.9185)	(145.9485)	(8.2816)	(3.5606)	
FTSE100	GJR	1.19E–05	6.53E–09	0.9173	0.0556	0.0308	55777.70
		(2.0353)	(6.1028)	(146.9978)	(7.5414)	(3.5798)	
SP500	GJR	7.63E–06	7.91E–09	0.906113	0.0354	0.0916	55464.89
		(1.2893)	(6.9886)	(142.6707)	(5.4628)	(8.9008)	

		CAC-UK	CAC-DAX	CAC-SP	UK-DAX	UK-SP	DAX-SP
a	Coefficient	0.0204	0.0196	0.0242	0.0195	0.0202	0.0185
	t-statistics	(6.2576)	(6.0180)	(5.6258)	(7.0197)	(6.1050)	(4.5319)
b	Coefficient	0.9623	0.9622	0.9550	0.9698	0.9671	0.9696
	t-statistics	(172.9806)	(154.7314)	(113.6921)	(231.7372)	(185.0174)	(126.2658)
c	Coefficient	0.0020	0.0007	0.0020	0.0015	0.0029	0.0009
	t-statistics	(4.1162)	(3.3530)	(2.4100)	(3.6896)	(5.1929)	(1.6924)
Log likelihood		112821.8	112279.1	111177.6	111851.6	114632.9	110891.5

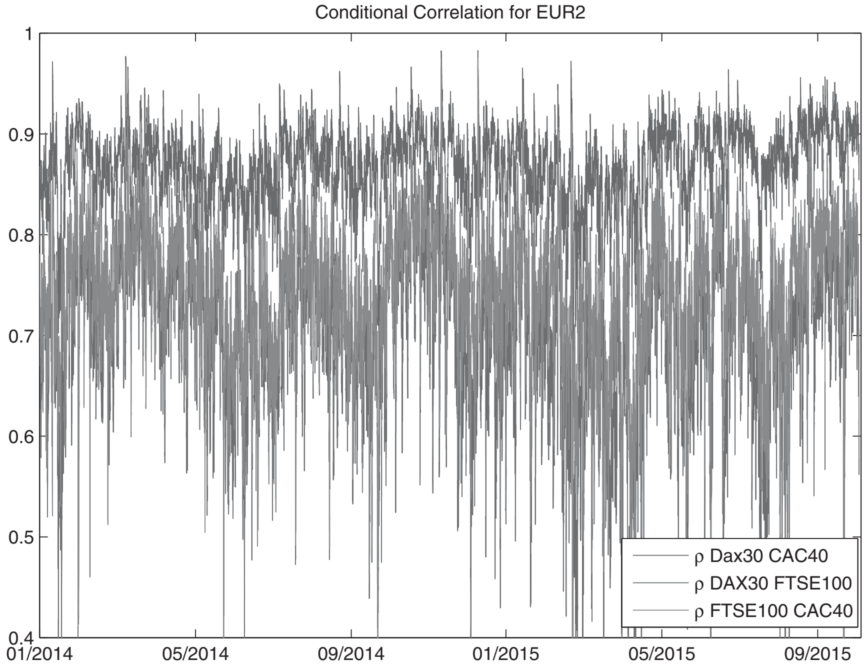

FIGURE 1. Conditional correlation for NOTH over the benchmark period.

Figure 1 shows that there is high volatility in the conditional correlation in comparison with the OTH time interval. In particular, the highest conditional correlation is between the CAC40 and DAX30 pair for the two periods of time NOTH and OTH, again suggesting strong linkages between Paris and Frankfurt. The time-variation character associated with conditional correlation is also confirmed, indicating that the comovement process is continuous and evolves over time. Conditional correlations between the European markets decrease during the overlapping [14:30 to 16:30 (GMT)] period. For the crisis period, there is less volatility for the conditional correlation, and the level is very close for all the markets, suggesting higher integration between the market indices. For NOTH, the highest conditional correlation is also between the CAC40 and the DAX30 pair.

While these different findings indicate significant comovements between intradaily stock prices, and offer some evidence of intraday systemic risk transmission, the contribution to systemic risk is not directly measured, and we might wonder about the variation in market interactions when we only focus on extreme market risk. To improve this analysis and directly evaluate the contribution to systemic risk, we examine the interaction between distribution tails through a quantile regression approach. To this end, we applied the MES, which is a nonparametric approach.

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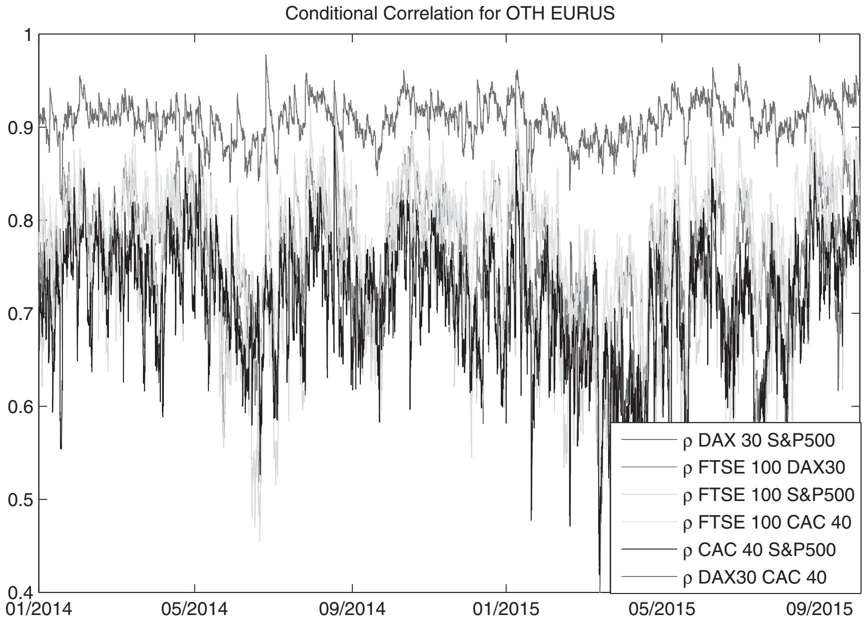

FIGURE 2. Conditional correlation for OTH over the benchmark period.

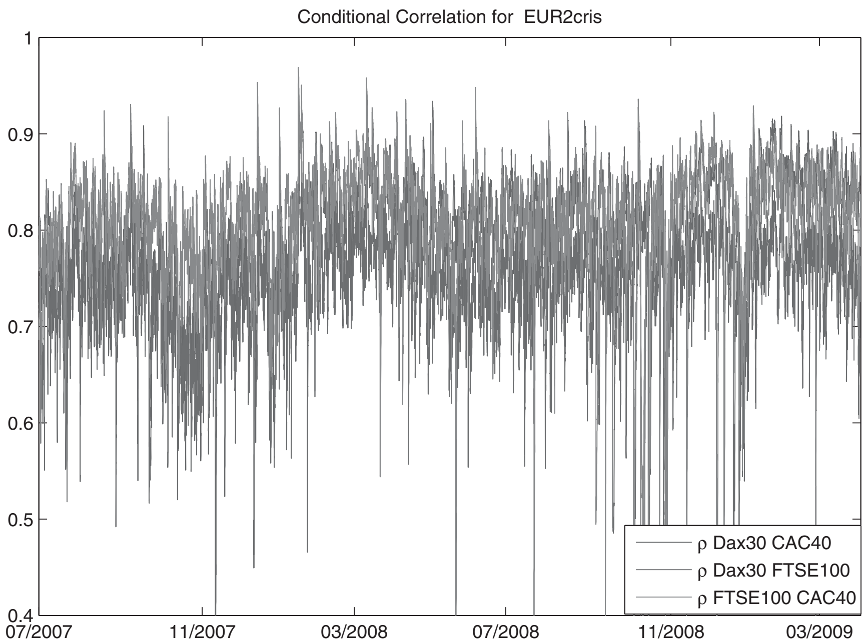

FIGURE 3. Conditional correlation for NOTH over crisis period.

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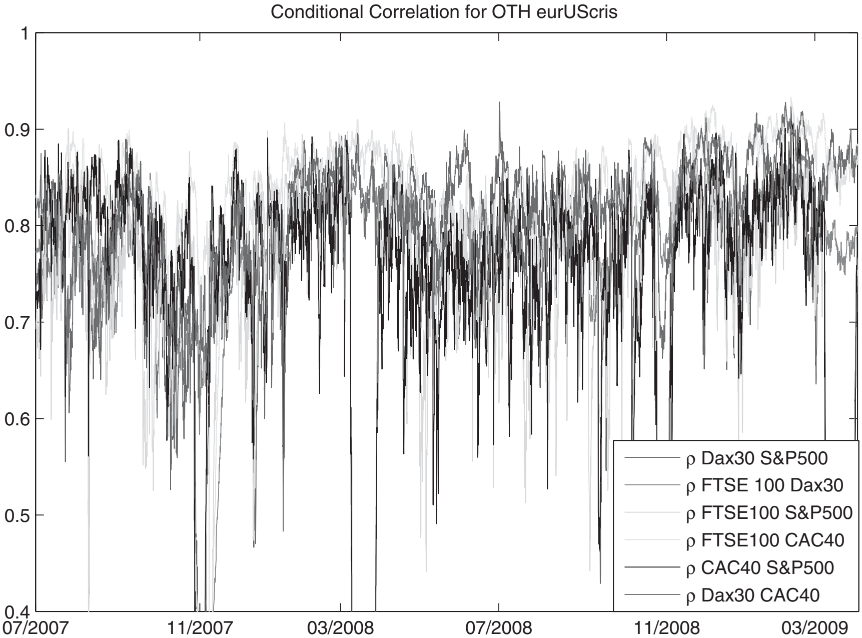

FIGURE 4. Conditional correlation for OTH over the crisis period.

The margin expected shortfall analysis. We computed the MES for each stock index under consideration during nonoverlapping trading hours and overlapping trading hours. We also computed the MES statistics for the two samples under consideration: the crisis period and the benchmark period. We reported the main results in Figures 5, 6, 7 and 8.

During the benchmark period, it seems that variations in the DAX30 have more impact than the FTSE100 on extreme variations in the CAC40 index. For the DAX30, the CAC40 has the most impact, while for the FTSE100, the impact of the CAC40 and the DAX30 are similar.

Regarding the crisis sample, we noted two clearly differentiated phases. Over the periods February 2008 to November 2008, the contribution to systemic risk for all market indices increased, while their contribution was moderate during the rest of the period under consideration.

During this sample period, we mainly found that the DAX30 has the highest impact on the extreme risk of the other markets. The MES level also generally increases during overlapping hours. This means that extreme risk increases and systemic risk transmission is higher when the US market is open.

During the crisis, two subperiods that can be clearly distinguished are those before and after September 2008, which corresponds approximately to Lehman Brothers' bankruptcy. After this event, the contribution to systemic risk increased for all the market indices and was very close for all the markets under consideration.

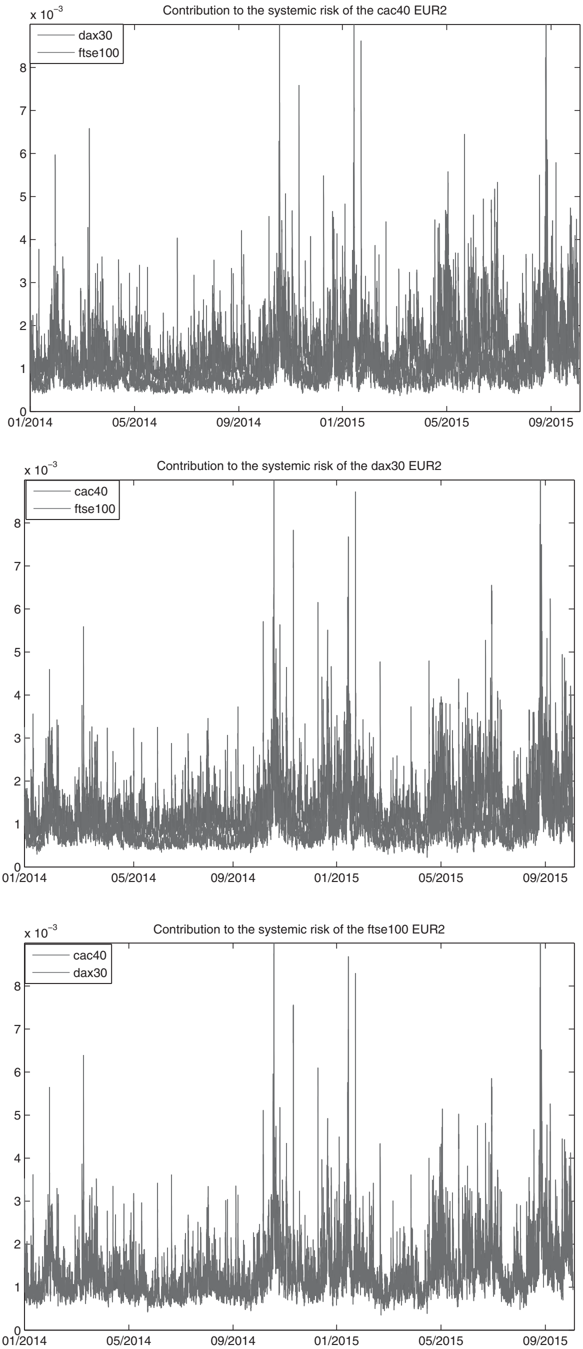

FIGURE 5. MES dynamics for NOTH over the benchmark period.

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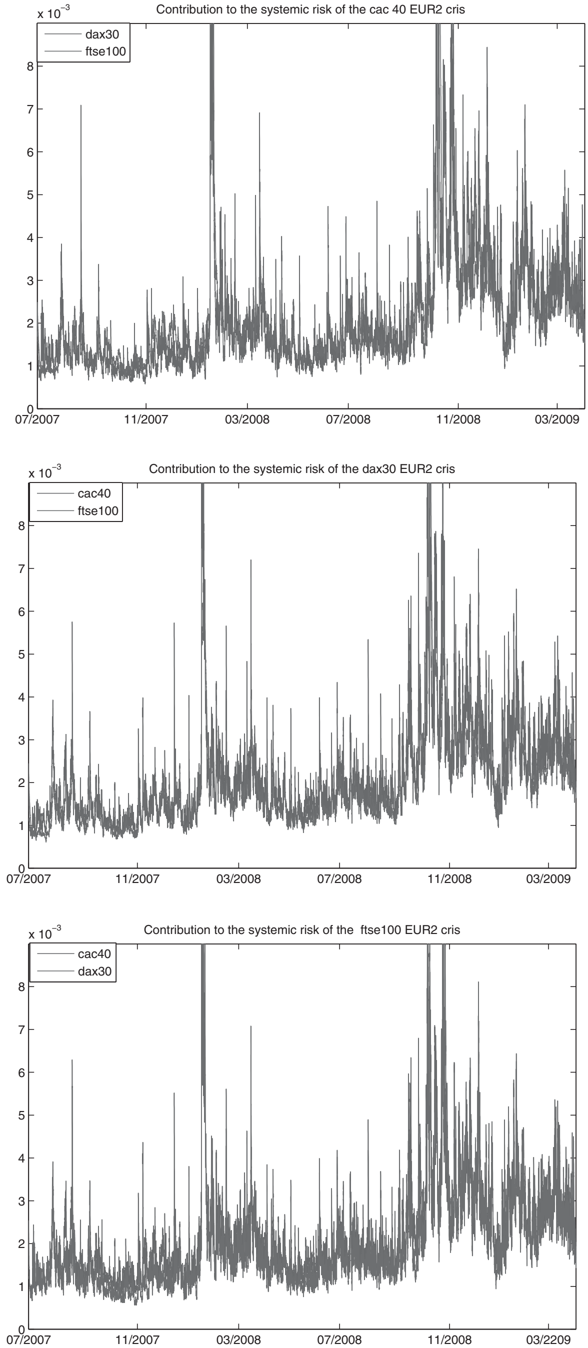

FIGURE 6. MES dynamics for NOTH during the crisis period.

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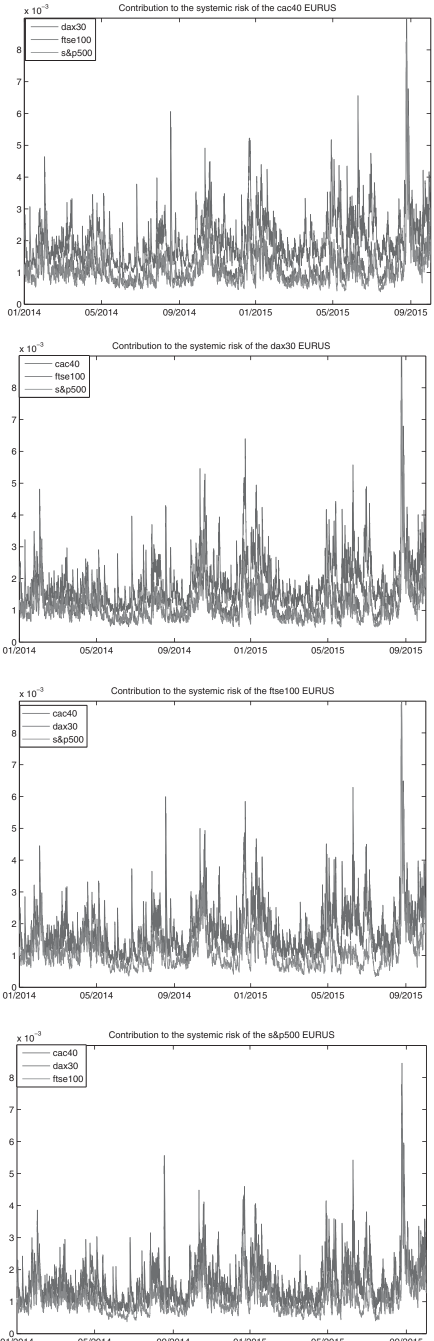

FIGURE 7. MES dynamics for OTH during the benchmark period.

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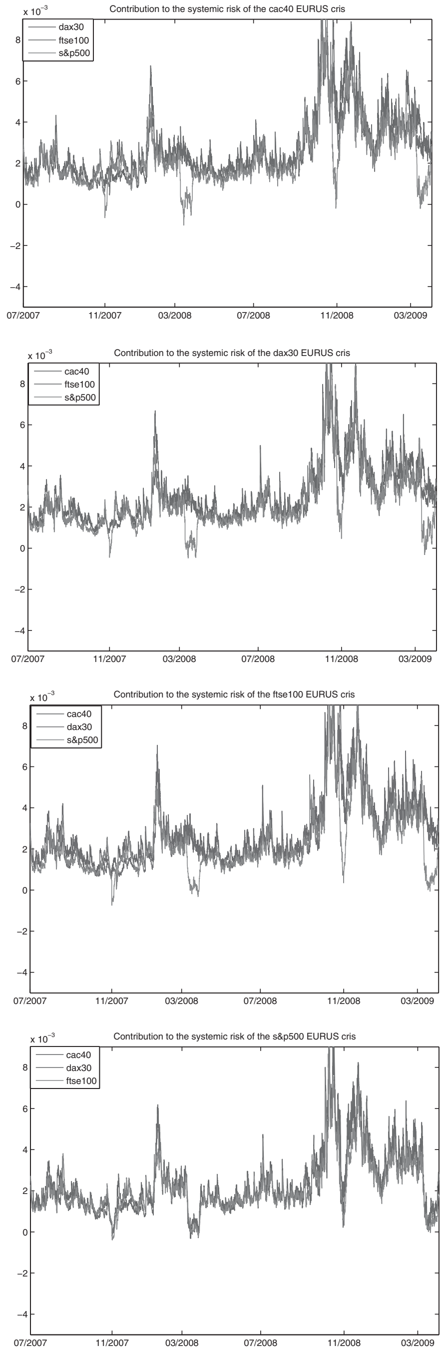

FIGURE 8. MES dynamics for OTH during the crisis period.

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5. CONCLUDING REMARKS

This paper set out to investigate stock price comovements and systemic risk transmission across the United States and three major stock markets (France, Germany, and the United Kingdom). To do this, we used recent and original HFD covering the subprime period and a recent, calm (benchmark) period. Formally, two different econometric methodologies were applied, the ADCC-GARCH model and the MES, to evaluate stock price comovements and measure systemic risk contributions, respectively. To our knowledge, this paper is the first to investigate these two hypotheses by using OTH and NOTH. Accordingly, our investigation points to several interesting findings. First, we show significant time-varying and asymmetrical stock return linkages, indicating that markets are linked, and that their reaction to negative shocks differs from their reaction to positive shocks. Second, the MES approach shows that both European and US indexes significantly contribute to each other's systemic risk, with a strong contribution from Frankfurt to the French and US markets, especially after the collapse of Lehman Brothers. Third and perhaps most interestingly, both analyses indicate that stock return linkages and contributions to systemic risk significantly increase during the crisis period and with the opening of the US market, which means that propagation of systemic risk is higher during OTH. These findings have at least two implications. On the one hand, it is clear that controlling the openness of the US market would help to forecast further systemic risk across European markets. On the other hand, unlike Idier et al. (2014), we consider that the MES could be useful to better forecast and avoid further market downturns and crises induced by increased systemic risk between stock markets.

NOTES

1. In this context, the Basel III committee suggests completing traditional microprudential measures with a list of macroprudential rules to take systemic risk into account.
2. See Kuester et al. (2006) for more details on the prediction performance of these different measures.
3. HFT refers to the introduction of new traders by using computer algorithms and computerized trading. For Stothard (2012), HFT represents 40% of total European and 50% of total US equity trading orders.
4. HFD was used first by Harris (1986) Taylor and Xu (1997), Anderson et al. (1998) and Schwert (1998). The first two studies used 5-minute returns, while Schwert (1998) worked with 15-minute returns.
5. See Arouri and Jawadi (2007) for a nonexhaustive literature review.
6. See Bekaert and Wu (2000) for a literature survey on volatility spillovers.
7. There are still too few studies investigating price comovements with HFD.
8. See Bauwens et al. (2006) for a study of multivariate GARCH models.
9. σ_t is not limited to the standard univariate GARCH (p, q) and can include any GARCH process with Gaussian distributed errors that satisfy appropriate stationarity conditions, ensuring the existence of unconditional variance.
10. For more details on the advantages of using quantiles, see Krause and Paolella (2014).
11. See Banulescu and Dumitrescu (2015) for more details on the Component Expected Shortfall.

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