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Kari Harju & Syed Mujahid Hussain

*INTRADAY LINKAGES ACROSS INTERNATIONAL EQUITY MARKETS*

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JEL Classification: G14, G15



Kari Harju & Syed Mujahid Hussain
Department of Finance, Vasa
Swedish School of Economics and Business Administration
P.O.Box 287
65101 Vasa, Finland

Distributor:

Library
Swedish School of Economics and Business Administration
P.O.Box 479
00101 Helsinki
Finland

Phone: +358-9-431 33 376, +358-9-431 33 265
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# Intraday Linkages across International Equity Markets

**Kari Harju**

*Department of Finance, Hanken-Swedish School of Economics and Business Administration, PB 287, 65101, Vasa, Finland*

*e-mail: kari.harju@hanken.fi*

**Syed Mujahid Hussain***

*Department of Finance, Hanken-Swedish School of Economics and Business Administration, PB 287, 65101, Vasa, Finland*

*e-mail: syed.mujahid@hanken.fi*

**Abstract**

Utilizing concurrent 5-minute returns, the intraday dynamics and inter-market dependencies in international equity markets were investigated. A strong intraday cyclical autocorrelation structure in the volatility process was observed to be caused by the diurnal pattern. A major rise in contemporaneous cross correlation among European stock markets was also noticed to follow the opening of the New York Stock Exchange. Furthermore, the results indicated that the returns for UK and Germany responded to each other's innovations, both in terms of the first and second moment dependencies. In contrast to earlier research, the US stock market did not cause significant volatility spillover to the European markets.

**Key words:** Intraday; diurnal pattern; conditional mean; volatility spillovers; Flexible Fourier Form; VAR; EGARCH; asymmetry

**JEL classifications:** *G14, G15*

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*Corresponding author

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## 1. Introduction

An understanding of inter-market volatility is important for the pricing of securities within and across the markets, for international diversification strategies, for hedging strategies and for regulatory policy. The crash of October 1987 triggered the phenomenon of information spillovers across national markets.[1] Since then volatility spillovers across markets have been reported in many studies. Most of these studies fall mainly into three categories. One strand of this literature investigated inter-market dependencies using daily open-to-close or close-to-open returns due to the sequential trading caused by different time zones. For example, Hamao et al. (1990) and Koutmos and Booth (1995), focused on spillovers across New York, London and Tokyo. Their findings suggested that stock markets are generally sensitive to news originating in other markets. Knif et al. (1999) investigated lead-lag relationships between international stock markets by taking account of the different trading hours of stock exchanges. Their findings showed that New York is evidently the most influential market affecting all other stock exchanges in Europe and in the Asian-Pacific. A second group of papers is concerned with the lead-lag relations between two or more markets that trade simultaneously. Kuotmos (1996) and Kanas (1998) documented significant volatility transmissions across major European markets. They also reported that in most instances the volatility transmission mechanism was asymmetric, i.e. negative innovations in a given market increase volatility in the next market to trade considerably more than positive innovations. Finally, some studies have explored the role of information flow and other microstructure variables as determinants of intraday return volatility [e.g. Andersen et al. (2002)].

This paper investigates the intraday return and volatility interaction between three international equity markets using carefully constructed 5-minute intraday returns from September 2000 to August 2003. The question whether return and volatility in one market predicts the return and volatility in the other market during contemporaneous trading hours is analyzed. The stock markets of UK and Germany operate concurrently for at least eight hours during every trading day,

[1] See the survey by Roll (1989).

whereas the US market shares at least two hours of concurrent trading with these European markets. This fact enables modeling the dynamic first and second moment behavior among the European markets in the presence and absence of the US market's operation. Two major European equity markets, Frankfurt and London, share the same trading hours and are closely linked through economic fundamentals. Furthermore, earlier research has shown that the US macroeconomic announcements significantly affected the return and volatility process in European equity markets [Harju and Hussain (2006), Nikkinen et al (2004)]. These findings indicate that significant spillovers among these three national stock markets may be attributed to a high degree of interdependence.

Since a shock in a national market may be transmitted to another market within a very short period of time, it is essential to employ high-frequency data. There were fewer studies that have modeled dynamic intraday interactions between equity markets using high-frequency data. Engle and Susmel (1994) examined the relationship between the New York and London stock markets using concurrent hourly returns. They did not report any significant evidence of volatility spillovers between both markets. Jeong (1999) employed overlapping high-frequency data (5-minute returns during 2 hours of overlapping trading) to explore the transmission pattern of intraday volatility among the US, Canadian and UK markets. His results showed that there existed a strong inter-market dependence, implying that the information produced in any market is affecting other cross-border markets. Both of these articles have utilized the ARCH methodology. However, Jeong (1999) did not take into account the diurnal pattern, which could have led into spurious dependencies.

There are several plausible explanations mentioned in financial literature for the interdependence between the returns and the volatilities of two equity markets. Market contagion implies that enthusiasm for stocks in one market brings about enthusiasm for stocks in other markets, regardless of the evolution of the market fundamentals.[2] Another possible explanation is

[2] For a detailed discussion see Forbes and Rigobon (2002).

financial market integration. One interpretation of financial market integration is that shocks are propagated through real economic linkages between countries, such as trade [see for example Connolly and Wang (1998)]. However, investigating the specific factor driving potential spillovers during concurrent trading hours was beyond the scope of this paper.

The main findings are as follows: First, the New York Stock Exchange (NYSE) typically affected the diurnal pattern in two major European markets. This potential effect of the US market's opening pointed to constant volatility shift and a significant rise in correlations structure within European markets. Second, significant and reciprocal intraday spillovers are reported across two European equity markets. Finally, the US stock market impact could largely be described as a contemporaneous effect, i.e. the return correlation among the UK and Germany rose significantly during the afternoon trading following the US stock market opening. In contrast to earlier findings no significant volatility spillover from the US to European stock markets is observed. The concurrent intraday returns are found to be informative as they demonstrated significant cross correlation among the three equity markets.

This paper contributes to the existing literature in mainly two aspects. First, it demonstrates high level of contemporaneous interdependence among intraday returns. The correlation coefficients reported are comparable to those found on lower data aggregations. This interdependence increased significantly following the opening of the New York stock exchange. Thus, this article extends the work by Koutmos (1996) and Kanas (1998) by presenting new evidence of the high frequency interdependence among the major European equity markets. Second, it takes into account strong intraday seasonalities observed in intraday data. Finally, the US effect is explicitly modeled using SP500 and macroeconomic surprises, hence controlling for any overlapping impact on European markets.

The rest of the paper is organized as follows. The data are described in section two. Some stylized facts of intraday data are presented in section three. Cross correlations are discussed in section four. The methodological framework is outlined in section five. The major empirical findings are reported in section six and a summary and conclusion of the paper are in section seven.

## 2. Data

The primary dataset consisted of 5-minute price quotes on three major equity indices from September 1, 2000 through August 29, 2003, totaling three years.[3] The indices are XDAX of Germany, FT100 of the UK, and SP500 of the US. These indices were selected since they offer comparability to earlier research. The two European markets share the same opening time, i.e. 9.00 CET[4], whereas the closing times vary. Typically, concurrent trading continues until 17.30, a total of eight and half hours per day. The New York Stock Exchange (NYSE) opens at 15.30 CET, sharing at least two hours of concurrent trading with the European counterparts. The continuously compounded returns were calculated as $R_{i,t} = 100\times\log(P_{i,t}/P_{i,t-1})$, where $R_{i,t}$ and $P_{i,t,}$ are the return and price level on index i at time t, respectively. The data were filtered for outliers and other anomalies, more specifically September 11 effect and observations influenced by brief lapses in Reuters data feed. Very occasionally, linear interpolation was used to replace solitary 5-minute price quotes to obtain strictly periodical data required by the filtration technique discussed in the next section. Finally, the total number of observations summed up to 56 160 (702 days) for SP500 stock index, 73 851 (717 days) for FT100 stock index, and 99 225 (735 days) for XDAX.

### 2.1 Stylized facts of high frequency data

The usage of high frequency data is interesting and persuasive since it may reveal new information that is not observable in lower data aggregations. However it poses new challenges too. The analyses of these data are complicated by irregular temporal spacing, price discreteness, diurnal

[3] The data were obtained from Olsen Data, Switzerland.
[4] Hereafter all trading times are given in Central European Time, CET.

pattern and complex, long-lived dependence [e.g. Engle and Russel (2002)]. It has been widely documented that return volatilities vary systematically over the trading day, exhibiting typically a U-shaped pattern of volatility. Among the first to document this diurnal pattern were Wood et al. (1985) and Harris (1986a). The pronounced periodic structure in the return volatility has a strong impact on the dynamic properties of high frequency returns. Andersen and Bollerslev (1997) showed that standard time series methods applied to high frequency returns may give rise to erroneous inference about the return volatility dynamics. The existence of pronounced intraday patterns has been shown in average volatility over the trading day across the stock markets. Moreover, correcting for the pronounced periodic pattern is a critical issue in examining lead-lag relations between equity markets that trade simultaneously.

As seen in Table 1, the average returns during this three-year period were slightly negative for all markets. Retrospectively, this period could well be characterized as a bear market. The 5-minute mean return was practically zero for all markets and dwarfed by its standard deviation. In contrast, the minimum and maximum returns were sizeable, especially when associated with the substantial change of total market value within such a short time period. If pure geometric Brownian motion would be the underlying return generating process, the minimums and maximums would be expected to diminish in size, as the frequencies become higher. In comparison to lower data aggregations, no considerable reduction in extreme values was observed. Several different intervals were investigated, although not reported in this study. The minimum 5-minute return for XDAX was 7.27%, which is 40 times greater than its respective standard deviation. The existence of jumps and discontinuities in high frequency data is therefore evident. The first order autocorrelation, AC(1), was slightly positive for all markets, implying some evidence of stale prices. The positive autocorrelation of the squared returns indicates presence of volatility clustering. The augmented Dickey-Fuller test rejected the null hypothesis of nonstationarity for all three return series.

**Table 1**

Summary statistics for 5-minute stock index returns

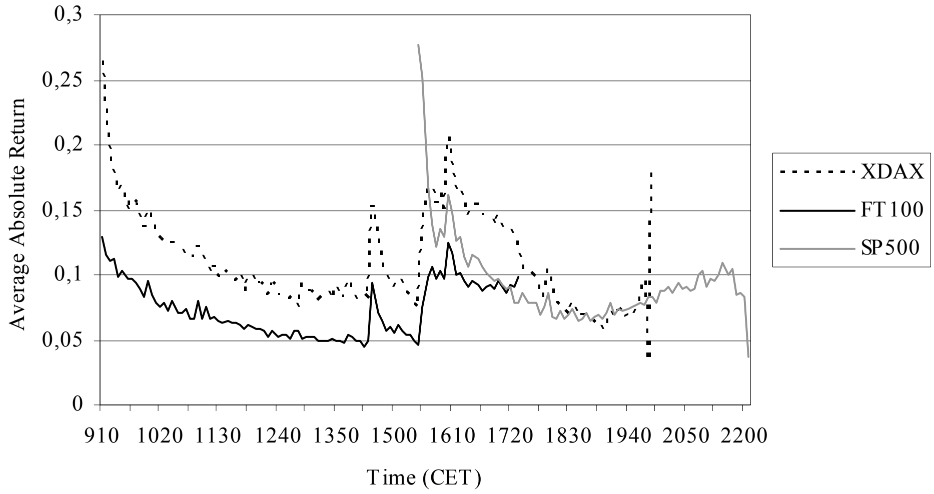
FT100, XDAX and SP500 are equity market indices for the UK, Germany and the US, respectively.

| | FT100 | XDAX | SP500 |
|---|---|---|---|
| Mean | -0,0006 | -0,0007 | -0,0007 |
| Maximum | 3,65 | 4,68 | 3,51 |
| Minimum | -3,74 | -7,27 | -5,14 |
| Standard Deviation | 0,13 | 0,18 | 0,14 |
| Skewness | -0,44 | -0,55 | -0,83 |
| Kurtosis | 68,81 | 58,78 | 71,26 |
| | | | |
| Return autocorrelation (lag 1) | 0,051 | 0,018 | 0,071 |
| Return autocorrelation (lag 2) | 0,001 | -0,019 | 0,005 |
| Squarred return autocorrelation (lag 1) | 0,194 | 0,065 | 0,04 |
| Squarred return autocorrelation (lag 2) | 0,062 | 0,035 | 0,018 |
| Augmented Dickey-Fuller test statistic | -151 | -225 | -221 |
| Number of observations | 73851 | 99225 | 56160 |
| Percentage of zero returns | 1,17 | 1,00 | 2,37 |

The intraday seasonalities in average absolute returns are depicted in Figure 1. The calendar effects were obvious in all three markets, while another noticeable feature in Figure 1 was the apparent co movement of these equity markets.[5] Furthermore, in line with Andersen and Bollerslev (1997), the autocorrelation pattern of absolute average returns and squared returns were analyzed. The correlograms of the absolute and the squared returns are presented in Figures A1 and A2 in Appendix A, respectively. For each stock market the series was lagged for 10 trading days. This operation revealed an intriguing intraday dependence. The high autocorrelations were clustered around the opening and closing of each trading day, except for XDAX that displayed a pattern resembling a W. The source for this characteristic was the intraday seasonal volatility pattern depicted in Figure 1, i.e. high volatilities at the opening and closing of the trading day caused the autocorrelation pattern to behave in a cyclical manner. This dependence structure was particularly exposed in the absolute returns since it contained more serial correlation than the squared return. This phenomenon was dubbed “Taylor effect” as Taylor (1986) found that absolute returns of speculative assets have significant serial correlation over long horizons. The 10-day correlogram

[5] For detailed discussion on the diurnal pattern see Harju and Hussain (2006).

also illustrated the well-known volatility persistence. These distinct systematic fluctuations provided an initial indication that direct ARCH type modeling of the intraday return volatility would be problematic. As noted by Andersen and Bollerslev (1997), “standard ARCH models imply a geometric decay in the return autocorrelation structure and simply cannot accommodate strong regular cyclical patterns”. To avoid potential biases further in the study, the seasonal component was filtered from the returns. The next section introduces the routine of deseasonalizing intraday returns.




**3. Flexible Fourier Form of seasonal volatility**

The intraday seasonal patterns in the volatility of financial markets have important implications for modeling the volatility of high frequency returns. The patterns were so distinctive that there was a strong need for taking them into account before attempting to model the dynamics of intraday volatility. Andersen and Bollerslev (1997, 1998) note that standard time series models of volatility have proven inadequate when applied to high-frequency returns data, and that the reason for this is simply the systematic pattern in average volatility across the trading day. They also suggest a practical method for the estimation of the intraday seasonal pattern. The seasonal could be estimated either by simply averaging the volatility over the number of trading days for each intraday period in line with Taylor and Xu (1997), or by using the Flexible Fourier form (FFF) proposed by Gallant (1981, 1982).

Following Andersen and Bollerslev (1997, 1998), the following decomposition of the intraday returns was considered,[6]

$$R_{t,n} = E(R_{t,n}) + \frac{\sigma_t S_{t,n} Z_{t,n}}{N} \tag{1}$$

where $E(R_{t,n})$ is the expected 5-minute return, N refers to the number of return intervals per day and $Z_{t,n}$ being iid. with zero mean and unit variance. By squaring and taking logs of both sides in equation (1), $X_{t,n}$ is then defined as

$$X_{t,n} = 2\{\ln|R_{t,n} - E(R_{t,n})|\} - \ln(\sigma_t^2) + \ln(N^2) = \ln(S_{t,n}^2) + \ln(Z_{t,n}^2). \tag{2}$$

Replacing $E(R_{t,n})$ by the average of all intraday returns, and $\sigma_t$ by an estimate from a daily-realized volatility, $\hat{X}_{t,n}$ was obtained. The seasonal pattern was estimated by using ordinary least square estimation (OLS).

$$\hat{X}_{t,n} = f(\theta; t, n) + (\mu_{t,n}) \tag{4}$$

$$f(\theta; t, n) =$$

$$\sum_{j=0}^{J} \sigma_t^j \left[ (\mu_{0,j}) + \mu_{1,j}(n/N_1) + \mu_{2,j}(n^2/N_2) + \sum_{i=1}^{I} \lambda_{i,j} I_{t,n} \sum_{i=1}^{P} \left[ \gamma_{i,j} \cos(2\pi i n/N) + \delta_{i,j} \sin(2\pi i n/N) \right] \right], \tag{5}$$

[6] Detailed discussion on Flexible Fourier Form (FFF) is found in Andersen and Bollerslev (1997, 1998).

where $N_1 = (N+1)/2$, and $N_2 = (N+1)(N+2)/6$ are normalizing constants. Based on the Schwartz criterion the model for equity market returns sets $j = 1$, and $p = 2$. This specification allows the shape of the periodic pattern in the market to also depend on the overall level of the volatility. Also the combination of trigonometric functions and polynomial terms are likely to result in better approximation properties when estimating regularly recurring cycles. For the information variables $I_{t,n}$, major US macroeconomic news announcements were used to control for likely volatility spikes in the European equity markets.[7] These announcements consist of monthly and quarterly published data on expected and realized macro economic fundamentals, defining news as the difference between expectations and realizations. Furthermore, three time specific dummy variables were generally included to minimize the distortion that may otherwise arise from the distinct volatility periods shown in Figure 1. The intraday seasonal volatility pattern was then determined by using

$$S_{t,n} = \exp\left(\hat{f}_{t,n}/2\right). \tag{6}$$

The deseasonalized intraday returns were then obtained simply by $\tilde{R}_{t,n} \equiv R_{t,n} \big/ \hat{S}_{t,n}$ , while the standardized intraday returns were generated by $\hat{R}_{t,n} \equiv R_{t,n} / \hat{\sigma}_t \, \hat{S}_{t,n}$.

The resulting fit of the estimated seasonal component $\hat{S}_{t,n}$ in equation 6 is depicted in Figure B1 in Appendix B. Clearly, the Flexible Fourier Form representation provided an excellent overall characterization of the intraday periodicity. To observe how the filtration method affected the serial correlation, the return series was reinvestigated. The correlograms of deseasonalized and standardized absolute and squared returns are presented in Figure A1 and A2 in Appendix A. The autocorrelation pattern confirmed that the FFF has reduced the cyclical behavior considerably, although the long-lived persistence became even more apparent. This is particularly seen in the

[7] The eleven US macro economic announcements are Advance Durable Goods, Index of Leading Indicators, Consumer Price Index, Housing Starts, Industrial Production, Personal Income, Producer Price Index, Gross Domestic Product, Retail Sales, Trade Balance, and Unemployment Rate.

deseasonalized absolute returns which exhibited a long lived dependence structure, whereas the standardized squared returns displayed a clear decay in serial correlation. Based on these auxiliary measures, utilizing the standardized returns appeared more feasible, thus reducing the risk of spurious causality among the intraday stock returns.

## 4. Stock market correlations

Once the diurnal pattern had been filtered from the returns, all observations were combined to obtain contemporaneous 5-minute deseasonalized and standardized returns. Prior to modeling the first and second moment dependencies, the data were analyzed using simple measures to facilitate additional understanding. Table 2 provides a matrix of contemporaneous and lagged correlations between the three markets. The contemporaneous correlations between the stock markets demonstrated strong relationships, varying between 0.5 and 0.7. The high cross correlation coefficients suggested that intraday 5-minute index returns contained information, not able to be detected by means of univariate time series analysis. Thus, financial markets appeared to be highly integrated even on intraday level and individual stock markets seemed to adopt new information rapidly.

To capture the potential impact of US presence or absence on European stock markets, the trading day was divided into two different sub-samples, the first one reaching from 9.00 to 15.30 (US absence) and the second one from 15.35 to 17.30 (US presence). The contemporaneous 5-minute deseasonalized return correlation between FT100 and XDAX was 0.54 in the first sub-sample. In the second sample the correlation rose to 0.7. To test whether there was a significant break in the linear dependence structure, the following model was estimated using restricted least squares for sorted deseasonalized returns,

$$R_{t,FT100} = \alpha + \beta R_{t,XDAX} + \varepsilon_t . \qquad (7)$$

The breakpoint was set at 15.35 CET. The F-value of the Chows breakpoint test was 108.96, which gave formal support for the suggestion that there was an increase in linear return dependence between FT100 and XDAX after 15.30 CET. Similar result was obtained using standardized returns.

**Table 2.** Cross-correlogram of deseasonalized and standardized returns

Panel A. From 9.00 to 15.30 CET

| | Deseasonelized | | | Standardized | |
|---|---|---|---|---|---|
| | FT100 | XDAX | | FT100 | XDAX |
| FT100 | 1 | 0,54 | FT100 | 1,00 | 0,50 |
| XDAX | 0,54 | 1 | XDAX | 0,50 | 1,00 |
| FT100 $_{t-1}$ | 0,05 | 0,05 | FT100 $_{t-1}$ | 0,06 | 0,05 |
| XDAX $_{t-1}$ | 0,16 | 0,00 | XDAX $_{t-1}$ | 0,17 | 0,00 |

Panel B. From 15:35 to 17.30 CET

| | Deseasonelized | | | | Standardized | | |
|---|---|---|---|---|---|---|---|
| | FT100 | XDAX | SP500 | | FT100 | XDAX | SP500 |
| FT100 | 1 | | | FT100 | 1 | | |
| XDAX | 0,7 | 1 | | XDAX | 0,66 | 1 | |
| SP500 | 0,60 | 0,65 | 1 | SP500 | 0,59 | 0,66 | 1 |
| FT100 $_{t-1}$ | 0,04 | -0,02 | 0,06 | FT100 $_{t-1}$ | 0,04 | -0,02 | 0,05 |
| XDAX $_{t-1}$ | 0,13 | -0,05 | 0,09 | XDAX $_{t-1}$ | 0,14 | -0,04 | 0,08 |
| SP500 $_{t-1}$ | 0,08 | -0,02 | 0,06 | SP500 $_{t-1}$ | 0,10 | -0,01 | 0,06 |

Notes: Subscript t-1 denotes a lag of 5 minutes.

Both the increased return dependence and the sudden rise in European stock index volatilities occurring exactly at 15.30 suggested an existence of a common factor. Harju and Hussain (2006) demonstrate that the volatilities on major European equity markets were significantly affected by the opening of the NYSE. Building on the notion that the US market was the most important producer of information [Eun and Shim (1989); Theodossiou and Lee (1993); Ng (2000)], it seems reasonable to presume that the US market, proxied by SP500, caused the structural break in European equity markets.

The cross-autocorrelations indicate an asymmetry of lead/lag relationship between two European markets. XDAX seem to predict clearly more of the FT100 returns than vice versa. This relationship remained unaffected by the change in the sub-sample.

## 5. Research methodology

Simultaneous effects of price and volatility spillovers were estimated by the vector autoregressive-exponential GARCH (VAR-EGARCH) model. The Exponential GARCH model, introduced by Nelson (1990c), allows for asymmetric volatility impact on past standardized innovations, a feature often attributed to the behavior of stock market prices. Unlike the linear GARCH, there are no restrictions on the $\alpha_i$ and $\gamma_i$ parameters to ensure nonnegativity of the conditional variances. Moreover, this model allows for a simultaneous estimation of both the first and the second moment interdependencies. Let $R_{i,t}$, i = 1,…,n (i.e., 1 = UK, 2 = Germany, 3 = US) be the return for the market i at time t, where the return was calculated as $R_{i,t} = 100\times \ln (P_{i,t} / P_{i,t-1})$ and $P_{i,t}$ being the stock price of index $i$ at time $t$. A VAR-EGARCH model depicting price and volatility spillovers may be formulated as:

$$\mathrm{R}_{\mathrm{i,t}} = \beta_{\mathrm{i},0} + \sum_{\mathrm{j}=1}^{n} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t}\ ,\ \text{for i, j} = 1,\ldots,\text{n and } \varepsilon_t \middle| \Psi_{t-1} \sim MVN(0, \Sigma_t) \quad (8)$$

$$\sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)\}, \text{for i, j} = 1,\ldots,\text{n} \quad (9)$$

$$f_j(z_{j,t-1}) = \left(\left|z_{j,t-1}\right| - E\left(\left|z_{j,t-1}\right|\right) + \delta_j z_{j,t-1}\right), \text{for j} = 1,\ldots,\text{n}; \quad (10)$$

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t}\ , \text{for i, j} = 1,\ldots,\text{n and i} \neq \text{j}. \quad (11)$$

Where $\varepsilon_{i,t}$ represents the error term conditional on the past information set $\psi_{t-1}$ and the standardized innovation $z_{j,t}$ is defined as $\varepsilon_{j,t}/\sigma_{j,t}$. $\mu_{i,t}$, $\sigma^2_{j,t}$, and $\sigma_{ij,t}$ are the conditional mean, conditional variance and conditional covariance, respectively.

Equation (8) describes the returns of the three markets as a vector autoregression (VAR), where the conditional mean in each market is a function of past own returns as well as cross-market past returns. Lead/lag relationships are captured by coefficients $\beta_{i,j}$, for $i \neq j$. A significant $\beta_{i,j}$ coefficient would imply that market $j$ leads market $i$ or, equivalently, current returns could be used to predict future returns in market $i$.

The variance function in equation (9) allows its own (local) standardized innovations as well as regional standardized innovations to exert an asymmetric impact on the volatility of market *i*. Asymmetry was modeled by equation (10) and would be present if $\delta_j < 0$ and statistically significant. The term $|z_{j,t-1}| - E(|z_{j,t-1}|)$ measures the size effect and $\delta_j z_{j,t}$ measures the asymmetric or sign effect, also attributed as leverage effect. If $\delta_j$ is significantly negative, a negative $z_{j,t}$ will reinforce the size effect. The ratio $|-1+ \delta_j| / |1+ \delta_j|$ measures the leverage effect. Volatility spillover in our model is measured by $\alpha_{i,j}$ for i,j = 1,2,3 and $i \neq j$. A significant $\alpha_{i,j}$ implies volatility spillovers. If the $\delta_j$ is at the same time significantly negative this implies that negative innovations on market j will have higher impact on the volatility of market *i* than positive innovations, i.e. the volatility spillover is asymmetric. The correlation in (11) is assumed to be time-invariant, an assumption that reduces the number of parameters to be estimated. $\Sigma_t$ is the conditional $2 \times 2$ variance-covariance matrix.

## 6. Empirical Findings

The maximum likelihood estimates of the bivariate VAR-EGARCH model for standardized returns are reported separately for different sub-samples in Table 3 panel A and B. In addition, the results obtained using desasonalized returns are reported in Table C1 in Appendix C. The results obtained using deseasonalized returns showed high degree of volatility persistence, the $\gamma$ coefficient indicated a very long or nearly integrated memory process. This finding has been discussed widely in financial literature using high-frequency data that points to a slow hyperbolic rate of decay in the autocorrelation structure of the volatility process (see for example Andersen and Bollerslev, 1997). Furthermore, the Ljung-Box statistics provide some evidence of remaining arch-effect in the residuals. In comparison, the standardized returns exhibited lower persistence parameters ranging from 0.888 to 0.947 and the LB residual statistics in Table 3 confirmed the improved fit of the bivariate model. Due to the apparent long memory process of desasonalized absolute and squared returns exhibited also in Appendix A, a test was conducted in the following way. The first 20 trading days of the UK return series were removed. A bivariate VAR-EGARCH estimation was then performed on the UK and German return series, treating the returns as contemporaneous observations, to investigate whether volatility spillovers could be observed. The hypothesis was that no intraday spillovers should appear with a 20-days delay. The results revealed that the desasonalized returns still exhibited a significant volatility spillover, whereas for standardized returns no volatility spillovers were observed. Similar results were found when additional trading days were removed from either the UK or the German stock market returns. In order to avoid spurious spillovers resulting from the nearly integrated volatility processes, results using standardized returns are considered to provide more reliable estimates of the cross-market dependencies.

The bivariate model considered both price and volatility spillovers for the UK and Germany for concurrent trading hours between 9.00 and 15.30. The results presented in the upper panel A of Table 3 indicated significant return spillovers in both directions. The $\beta_{1,2}$ coefficient, estimating return spillovers from Germany to UK, was 0.218. This suggested that roughly 22% of the German return innovations were transferred to the British stock market whereas only 3.3% of the British return innovations were on average spilled over to the German market. The return correlation was 0.502, slightly less than the contemporaneous presented in Table 2. Concerning the second moment interdependencies, in addition to own past innovations (arch-effects), the volatility spillovers were clearly noticed in both directions. Thus the conditional variance in each market was affected by innovations coming from the other market. In line with earlier findings [e.g., Kuotmos (1996) and Kanas (1998)], the volatility transmission mechanism was asymmetric in both markets, confirming that both the size and the sign of the innovations are important determinants of the volatility transmission mechanism. The degree of asymmetry, on the basis of the estimated $\delta_j$ coefficients, is highest for Germany. Negative innovations increased the volatility approximately 1.47 times more than positive innovations.

Turning to the bivariate VAR-EGARCH estimates for two hours of concurrent afternoon trading between the UK, Germany and the US, it was important to note that after the opening of the SP500 at 15.30 CET, the correlation between the UK and German market rose significantly from 0.502 to 0.69. It was asserted that the opening of the NYSE induced greater contemporaneous interdependence between the two major European equity markets. The results presented in the panel B of Table 3 indicate significant price spillovers from both Germany and the US to the UK, whereas returns in the German equity market seemed generally unaffected (at 5% significance level) by past returns in any of the two markets. The US market's returns were influenced by the return process in the German equity market, while the UK market did not seem to have any significant influence on US returns.

Focusing on the parameters describing the conditional volatility in each market, the volatility spillovers between two European markets, the UK and Germany, were found to be significant, virtually unchanged from the upper panel of Table 3. In contrast to earlier findings [Jeong (1999)], the US market did not seem to have any significant predictive power on European stock market volatilities. Whereas, both European markets predicted the next period volatility in the US stock market.

The leverage effect, or asymmetric impact of past innovations on current volatility is significant in all instances, again lending support to the notion that volatility interactions across national stock markets may also be asymmetric. The degree of asymmetry varied from 1.18 to 1.77.

**Table 3.** Maximum likelihood estimates of the VAR-EGARCH for standardized returns

The maximum likelihood estimates were obtained using following bivariate VAR-EGARCH model for 5-minute standardized simultaneous returns. The intercepts are omitted here for convenience, however, may be obtained from authors upon request. The estimation was done assuming multivariate t-distribution with 5 degrees of freedom. $LB^2(n)$ and $AC^2(n)$ are the Ljung-Box statistics and autocorrelation coefficient for squared residuals respectively.

$$R_{it} = \beta_{i,0} + \sum_{j=1}^{n} \beta_{i,j} R_{j,t-1} + \varepsilon_{it}, \text{ for i, j} = 1,...,n \quad \text{and} \quad \sigma^2_{i,t} = \exp\{\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma^2_{i,t-1})\}, \text{ for i, j} = 1,...,n$$

**Panel A**. Estimates for UK and Germany for concurrent trading hours between 9.00 and 15.30 (CET) for the period September 1, 2000 through August 1, 2003.
**Panel B**. Estimates for UK, Germany and the US for concurrent trading hours between 15.30 and 17.30 (CET) for the period September 1, 2000 through August 1, 2003.

| | *UK* | | | *Germany* | |
|---|---|---|---|---|---|
| Panel A. Maximum likelihood estimates of bivariate VAR-EGARCH | | | | | |
| | Coefficient | T-Stat | | Coefficient | T-Stat |
| $\beta_{1,0}$ | 0.000 | 1.230 | $\beta_{2,0}$ | 0.000 | 0.231 |
| $\beta_{1,1}$ | -0.014 | -3.128 | $\beta_{2,1}$ | 0.033 | 10.001 |
| $\beta_{1,2}$ | 0.218 | 36.828 | $\beta_{2,2}$ | -0.048 | -10.263 |
| $\alpha_{1,0}$ | -0.562 | -18.058 | $\alpha_{2,0}$ | -0.430 | -15.297 |
| $\alpha_{1,1}$ | 0.152 | 25.073 | $\alpha_{2,1}$ | 0.044 | 9.082 |
| $\alpha_{1,2}$ | 0.060 | 10.335 | $\alpha_{2,2}$ | 0.110 | 19.097 |
| $\delta_1$ | -0.067 | -2.962 | $\delta_2$ | -0.191 | -6.143 |
| $\gamma_1$ | 0.925 | 228.157 | $\gamma_2$ | 0.947 | 276.733 |
| $\rho_{1,2}$ | 0.502 | 133.435 | | | |
| $R^2_{UK}$ | 0.028 | | $R^2_{GER}$ | 0.004 | |
| $LB^2_{UK}(2)$ | 4.8143 | | $LB^2_{GER}(2)$ | 29.535 | |
| $AC^2_{UK}(2)$ | -0.001 | | $AC^2_{GER}(2)$ | 0.005 | |

| *UK-Germany (Market 1,2)* | | | *UK-US (Market 1,3)* | | | *Germany-US (Market 2,3)* | | |
|---|---|---|---|---|---|---|---|---|
| Panel B. Maximum likelihood estimates of bivariate VAR-EGARCH | | | | | | | | |
| | Coefficient | T-Stat | | Coefficient | T-Stat | | Coefficient | T-Stat |
| $\beta_{1,1}$ | -0.090 | -9.338 | $\beta_{1,1}$ | -0.038 | -4.222 | $\beta_{2,2}$ | -0.055 | -5.468 |
| $\beta_{2,2}$ | -0.048 | -10.263 | $\beta_{3,3}$ | 0.037 | 3.986 | $\beta_{3,3}$ | 0.005 | 0.453 |
| $\beta_{1,2}$ | 0.239 | 19.559 | $\beta_{1,3}$ | 0.095 | 13.844 | $\beta_{2,3}$ | 0.012 | 1.933 |
| $\beta_{2,1}$ | 0.013 | 1.730 | $\beta_{3,1}$ | 0.004 | 0.331 | $\beta_{3,2}$ | 0.067 | 4.316 |
| $\alpha_{1,1}$ | 0.175 | 12.108 | $\alpha_{1,1}$ | 0.199 | 14.657 | $\alpha_{2,2}$ | 0.159 | 12.963 |
| $\alpha_{2,2}$ | 0.140 | 10.366 | $\alpha_{3,3}$ | 0.092 | 8.968 | $\alpha_{3,3}$ | 0.104 | 9.966 |
| $\alpha_{1,2}$ | 0.067 | 4.981 | $\alpha_{1,3}$ | 0.012 | 1.112 | $\alpha_{3,2}$ | 0.040 | 4.280 |
| $\alpha_{2,1}$ | 0.033 | 2.778 | $\alpha_{3,1}$ | 0.029 | 3.232 | $\alpha_{2,3}$ | 0.018 | 1.789 |
| $\delta_{1,2}$ | -0.084 | -2.055 | $\delta_{1,3}$ | -0.109 | -2.987 | $\delta_{2,3}$ | -0.195 | -4.985 |
| $\delta_{2,1}$ | -0.164 | -3.375 | $\delta_{3,1}$ | -0.280 | -4.766 | $\delta_{3,2}$ | -0.173 | -3.631 |
| $\gamma_1$ | 0.888 | 82.681 | $\gamma_1$ | 0.900 | 93.188 | $\gamma_2$ | 0.931 | 131.474 |
| $\gamma_2$ | 0.921 | 104.003 | $\gamma_3$ | 0.944 | 124.770 | $\gamma_3$ | 0.942 | 134.085 |
| $\rho_{1,2}$ | 0.690 | 144.096 | $\rho_{1,3}$ | 0.640 | 117.854 | $\rho_{2,3}$ | 0.747 | 182.736 |
| $R^2_{UK}$ | 0.026 | | $R^2_{UK}$ | 0.010 | | $R^2_{GER}$ | 0.003 | |
| $R^2_{GER}$ | 0.002 | | $R^2_{US}$ | 0.004 | | $R^2_{US}$ | 0.006 | |
| $LB^2_{UK}(2)$ | 9.537 | | $LB^2_{UK}(2)$ | 31.399 | | $LB^2_{GER}(2)$ | 12.274 | |
| $AC^2_{UK}(2)$ | 0.006 | | $AC^2_{UK}(2)$ | 0.009 | | $AC^2_{GER}(2)$ | -0.002 | |
| $LB^2_{GER}(2)$ | 20.896 | | $LB^2_{US}(2)$ | 5.995 | | $LB^2_{US}(2)$ | 2.579 | |
| $AC^2_{GER}(2)$ | 0.000 | | $AC^2_{US}(2)$ | 0.006 | | $AC^2_{US}(2)$ | 0.003 | |

A robustness check was performed by dividing the full dataset into sub samples of 2000 consecutive observations and estimating the same model on each sub sample. The examination revealed that the parameters were consistent both in terms of magnitude and sign. Furthermore, the significance of the parameters was virtually unchanged.

**7. Summary**

This paper explores the dynamic first and second moment linkages among international equity markets using 5-minute index returns from the equity markets of the UK, Germany and the US, for the period September, 2001 trough August, 2003. The sample was divided into two sub-samples according to time. The first sub-sample consisted of 5-minute return observations from the opening until 15.30 CET for two stock indices, FTSE 100 of the UK and XDAX of Germany, while the second sub-sample reached from 15.35 trough 17.30 (CET). This allowed the modeling of intraday dependencies of two major European markets in the absence and presence of the US stock market trading activity.

The main findings are as follows. The two European markets exhibited significant reciprocal return and volatility spillovers. This relationship appeared virtually unchanged by the presence or absence of the US market. The US stock market impact could largely be described as a contemporaneous effect, i.e. the return correlation among the UK and Germany rose significantly during the afternoon trading following the US stock market opening. In contrast to earlier findings, no significant volatility spillovers from the US to the European stock markets were observed. The concurrent intraday returns were found to be informative as they demonstrated substantial cross correlation among the three equity markets. Furthermore, taking into account the strong intraday seasonalities appeared essential when modeling intraday returns.

While interpreting the lead/lag relationships, the fact that these indices constitute different number of stocks, should be taken into consideration, due to potential influence of non synchronous trading. Further research is needed to investigate the causes of the reciprocal spillovers. In addition, the index constituents time varying covariance structure could be investigated for deeper understanding of the observed cross market dependencies on index data.

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# Appendix A

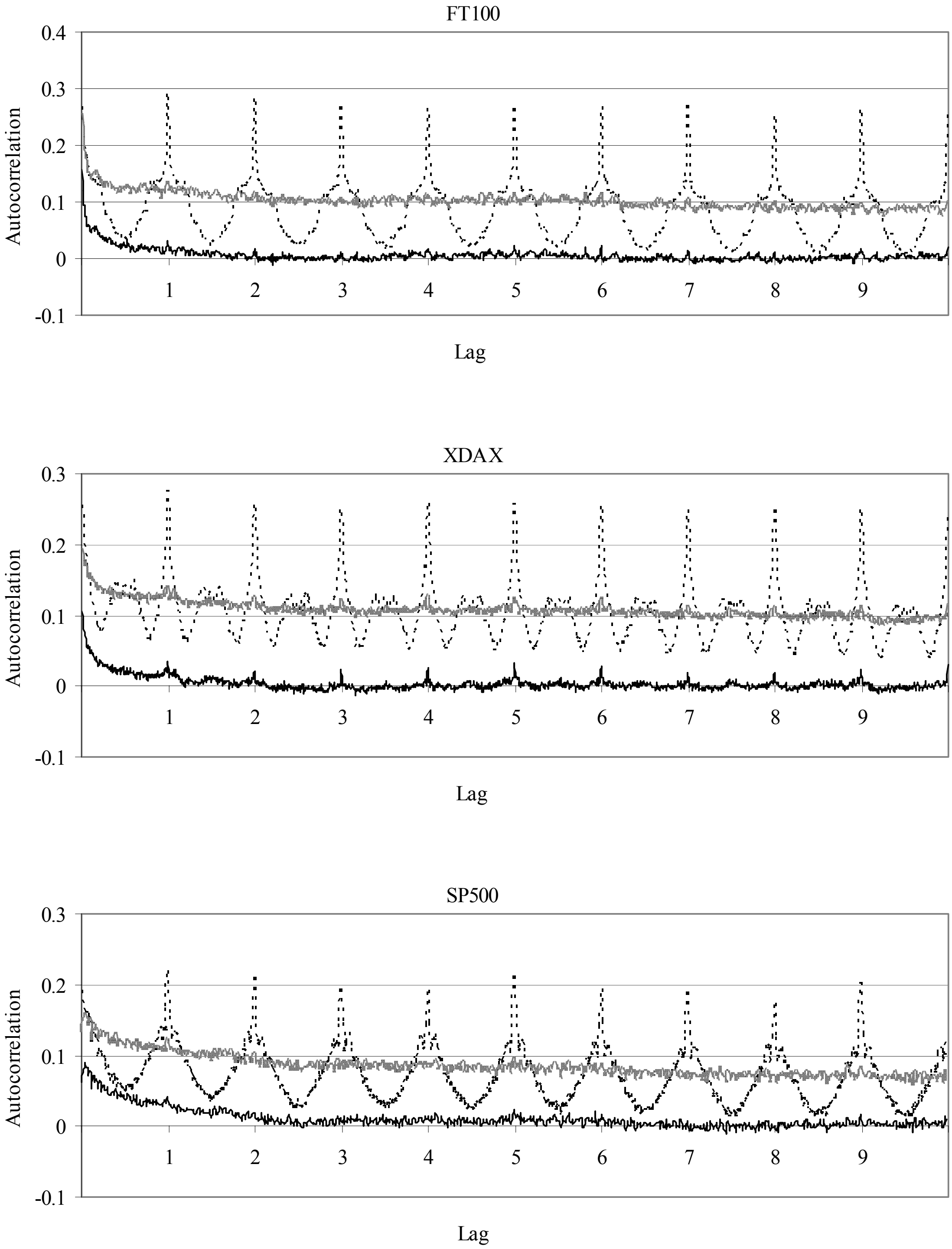
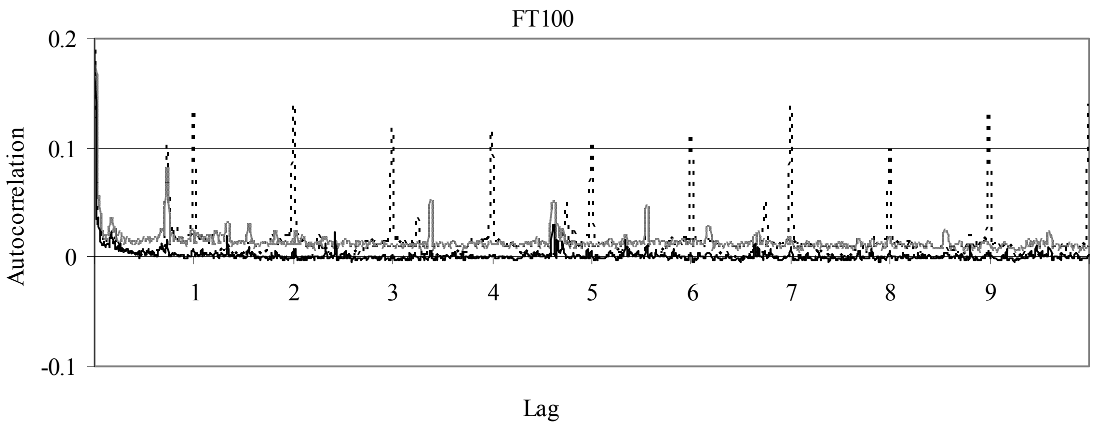
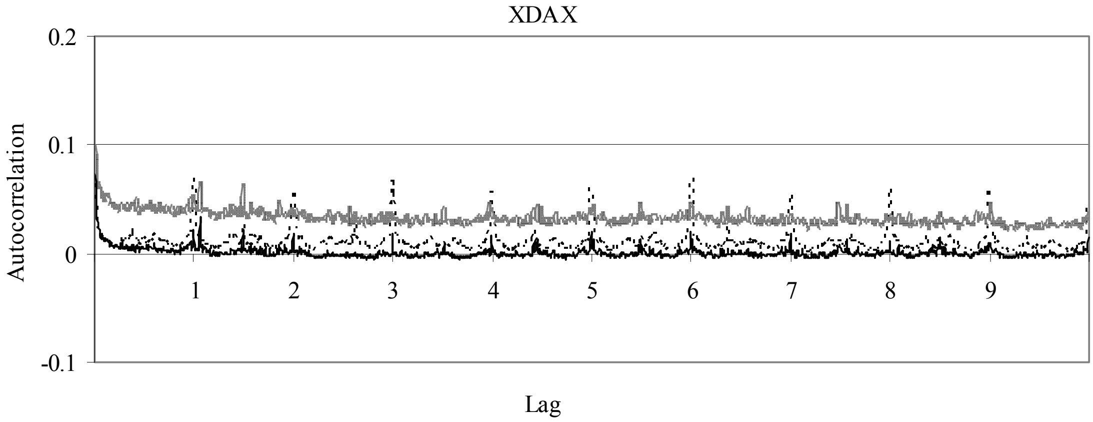



**Figure A1.** Autocorrelation pattern of 5-minute absolute, deseasonalized and standardized index returns
Notes: The maximum lag length depicted on x-axis is 10 trading days for all markets. The dashed line depicts the autocorrelation coefficients for absolute returns, the gray line deseasonalized absolute returns and the solid line standardized returns.



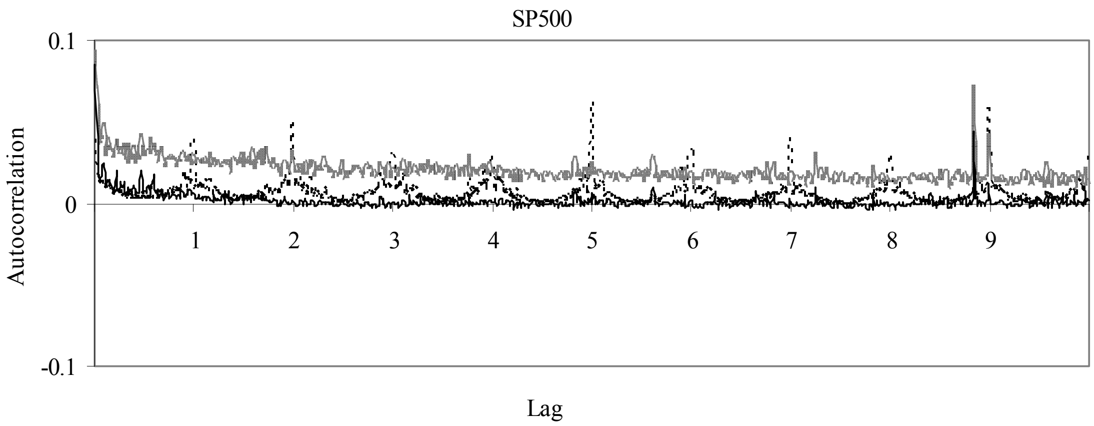




**Figure A2.** Autocorrelation pattern of 5-minute raw, deseasonalized and standardized squared index returns

Notes: The maximum lag length depicted on x-axis is 10 trading days for all markets. The dashed line depicts the autocorrelation coefficients for squared returns, the gray line deseasonalized squared returns and the solid line standardized squared returns.

## Appendix B

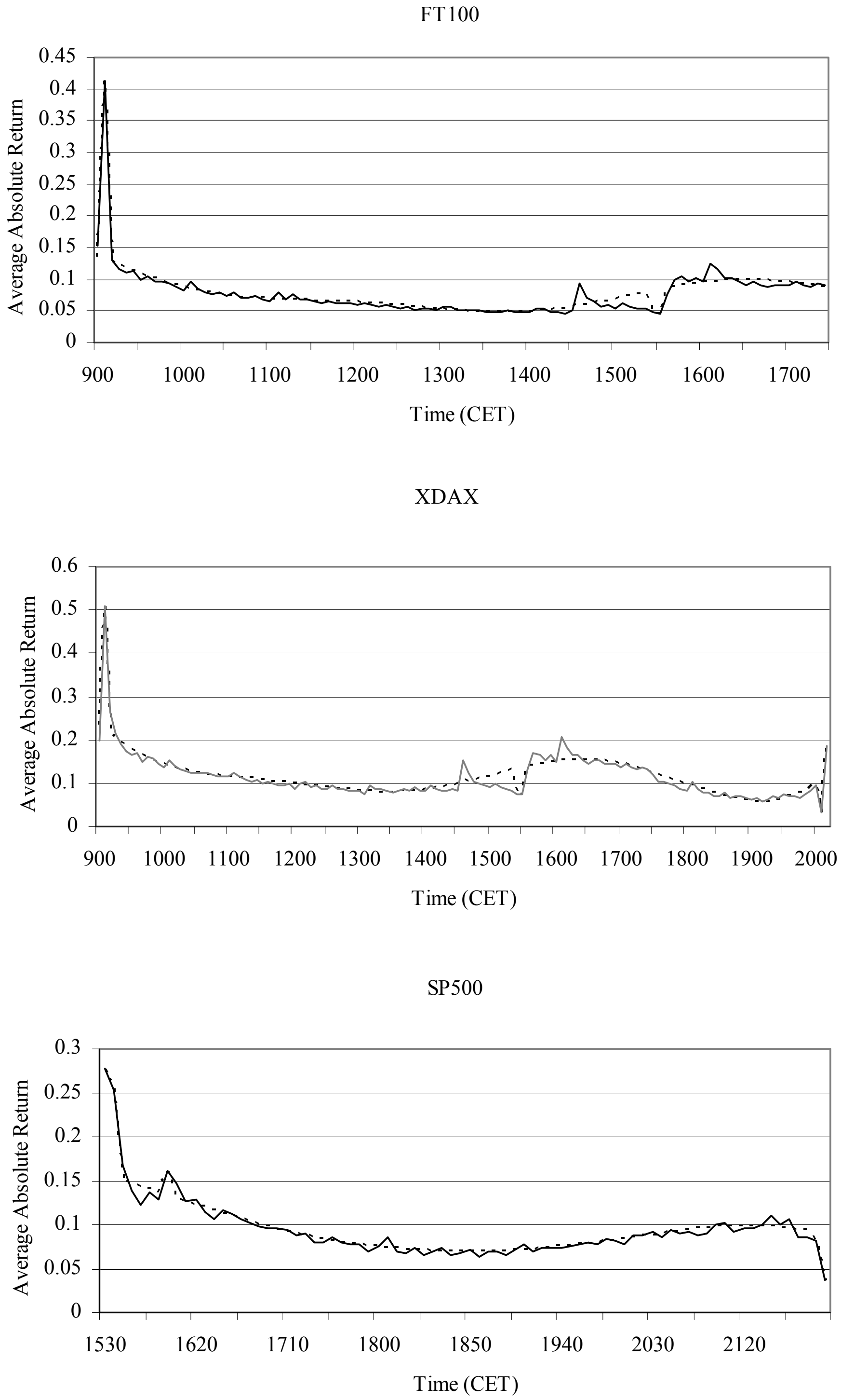



**Figure B1.** Actual and fitted intraday volatility pattern

Notes: Actual volatility pattern in solid line is the average absolute return for each 5-minute interval and the dashed line depicts the fitted seasonal component $S_{t,n}$, which is the FFF representation of the diurnal pattern.

## Appendix C

**Table C1.** Maximum likelihood estimates of the VAR-EGARCH for deseasonalized returns

The maximum likelihood estimates were obtained using following bivariate VAR-EGARCH model for 5-minute deseasonalized simultaneous returns. The intercepts are omitted here for convenience, however, may be obtained from authors upon request. The estimation was done assuming multivariate t-distribution with 5 degrees of freedom. $LB^2(n)$ and $AC^2(n)$ are the Ljung-Box statistics and autocorrelation coefficient for squared residuals respectively.

$$R_{it} = \beta_{i,0} + \sum_{j=1}^{n} \beta_{i,j} R_{j,t-1} + \varepsilon_{it}, \text{ for i, j} = 1,...,n \text{ and } \sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)\}, \text{ for i, j} = 1,...,n$$

**Panel A**. Estimates for UK and Germany for concurrent trading hours between 9.00 and 15.30 (CET) for the period September 1, 2000 through August 1, 2003.

**Panel B**. Estimates for UK, Germany and the US for concurrent trading hours between 15.30 and 17.30 (CET) for the period September 1, 2000 through August 1, 2003.

Panel A. Maximum likelihood estimates of bivariate VAR-EGARCH

| | *UK* Coefficient | *UK* T-Stat | | *Germany* Coefficient | *Germany* T-Stat |
|---|---|---|---|---|---|
| $\beta_{1,0}$ | 0.000 | 1.134 | $\beta_{2,0}$ | 0.000 | 0.506 |
| $\beta_{1,1}$ | -0.019 | -4.281 | $\beta_{2,1}$ | 0.051 | 9.640 |
| $\beta_{1,2}$ | 0.136 | 36.843 | $\beta_{2,2}$ | -0.047 | -10.419 |
| $\alpha_{1,0}$ | -0.111 | -16.898 | $\alpha_{2,0}$ | -0.074 | -16.094 |
| $\alpha_{1,1}$ | 0.108 | 27.494 | $\alpha_{2,1}$ | 0.049 | 14.682 |
| $\alpha_{1,2}$ | 0.042 | 11.049 | $\alpha_{2,2}$ | 0.072 | 19.829 |
| $\delta_1$ | -0.056 | -2.567 | $\delta_2$ | -0.192 | -5.936 |
| $\gamma_1$ | 0.984 | 1084.926 | $\gamma_2$ | 0.988 | 1476.069 |
| $\rho_{1,2}$ | 0.502 | 133.435 | | | |
| $R^2_{UK}$ | 0.027 | | $R^2_{GER}$ | 0.003 | |
| $LB^2_{UK}(2)$ | 14.184 | | $LB^2_{GER}(2)$ | 62.814 | |
| $AC^2_{UK}(2)$ | 0.003 | | $AC^2_{GER}(2)$ | 0.011 | |

Panel B. Maximum likelihood estimates of bivariate VAR-EGARCH

| *UK-Germany (Market 1,2)* | Coefficient | T-Stat | *UK-US (Market 1,3)* | Coefficient | T-Stat | *Germany-US (Market 2,3)* | Coefficient | T-Stat |
|---|---|---|---|---|---|---|---|---|
| $\beta_{1,1}$ | -0.088 | -9.365 | $\beta_{1,1}$ | -0.040 | -4.880 | $\beta_{2,2}$ | -0.061 | -6.397 |
| $\beta_{2,2}$ | -0.050 | -5.031 | $\beta_{3,3}$ | 0.034 | 3.705 | $\beta_{3,3}$ | 0.001 | 0.131 |
| $\beta_{1,2}$ | 0.151 | 20.584 | $\beta_{1,3}$ | 0.093 | 14.297 | $\beta_{2,3}$ | 0.016 | 1.901 |
| $\beta_{2,1}$ | 0.013 | 1.107 | $\beta_{3,1}$ | 0.009 | 0.824 | $\beta_{3,2}$ | 0.041 | 4.308 |
| $\alpha_{1,1}$ | 0.099 | 22.677 | $\alpha_{1,1}$ | 0.081 | 13.465 | $\alpha_{2,2}$ | 0.089 | 14.250 |
| $\alpha_{2,2}$ | 0.129 | 44.337 | $\alpha_{3,3}$ | 0.053 | 9.294 | $\alpha_{3,3}$ | 0.049 | 9.266 |
| $\alpha_{1,2}$ | 0.060 | 16.166 | $\alpha_{1,3}$ | 0.010 | 2.005 | $\alpha_{3,2}$ | 0.017 | 3.087 |
| $\alpha_{2,1}$ | 0.039 | 9.351 | $\alpha_{3,1}$ | 0.031 | 5.626 | $\alpha_{2,3}$ | 0.041 | 7.365 |
| $\delta_{1,2}$ | -0.120 | -4.571 | $\delta_{1,3}$ | -0.130 | -2.933 | $\delta_{2,3}$ | -0.116 | -3.111 |
| $\delta_{2,1}$ | -0.100 | -5.854 | $\delta_{3,1}$ | -0.265 | -4.395 | $\delta_{3,2}$ | -0.209 | -3.861 |
| $\gamma_1$ | 0.982 | 1011.007 | $\gamma_1$ | 0.994 | 1189.293 | $\gamma_2$ | 0.997 | 1825.964 |
| $\gamma_2$ | 0.981 | 993.837 | $\gamma_3$ | 0.992 | 941.536 | $\gamma_3$ | 0.996 | 1493.778 |
| $\rho_{1,2}$ | 0.6866 | 199.9503 | $\rho_{1,3}$ | 0.6423 | 117.8522 | $\rho_{2,3}$ | 0.7481 | 182.5395 |
| $R^2_{UK}$ | 0.022 | | $R^2_{UK}$ | 0.007 | | $R^2_{GER}$ | 0.002 | |
| $R^2_{GER}$ | 0.002 | | $R^2_{US}$ | 0.005 | | $R^2_{US}$ | 0.008 | |
| $LB^2_{UK}(2)$ | 78.244 | | $LB^2_{UK}(2)$ | 312.03 | | $LB^2_{GER}(2)$ | 52.524 | |
| $AC^2_{UK}(2)$ | 0.028 | | $AC^2_{UK}(2)$ | 0.047 | | $AC^2_{GER}(2)$ | 0.011 | |
| $LB^2_{GER}(2)$ | 64.954 | | $LB^2_{US}(2)$ | 15.346 | | $LB^2_{US}(2)$ | 8.9202 | |
| $AC^2_{GER}(2)$ | 0.009 | | $AC^2_{US}(2)$ | 0.012 | | $AC^2_{US}(2)$ | 0.007 | |

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