Intraday Linkages across International Equity Markets

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Abstract

We investigate the intraday dynamics and intermarket dependencies in international equity markets utilizing concurrent high frequency 5-minute returns. We observe a strong intraday cyclical autocorrelation structure in absolute returns caused by the diurnal pattern. Moreover, a major rise in volatility is also observed with the opening of the New York Stock Exchange. Our results indicate that both European markets, the UK and Germany, respond to each other's innovations. Furthermore, there are reciprocal spillovers from the U.S in terms of second moment dependencies on its European counterparts during two hours of concurrent trading.

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

JEL classifications: *G14, G15*

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1. Introduction

In this paper, we investigate the intraday return and volatility interaction between three international equity markets utilizing concurrent five-minute returns from September 2000 to August 2003. The stock markets of UK and Germany operate concurrently for at least eight hours during every trading day, whereas the U.S market shares at least two hours of concurrent trading with these European markets. This allows us to model the dynamic first and second moment behavior among the European markets in the presence and absence of the US market's operation.

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 has triggered the phenomena of information spillovers across national markets.[1] Since then, an enormous amount of research has focused on intermarket volatility and whether there is an association between volatility in one market and volatility in other markets. Most of these studies fall mainly into three categories. The first strand of this literature investigates intermarket 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), focus on spillovers across New York, London and Tokyo. Their findings suggest that stock markets are generally sensitive to news originating in other markets. Kinf et al. (1999) investigate lead-lag relationships between international stock markets by taking account of the different trading hours of stock exchanges. Their findings suggest 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) document significant volatility transmissions across major European markets. They also report that in most instances the volatility

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

transmission mechanism is 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 explore the role of information flow and other microstructure variables as determinants of intraday return volatility [e.g. Andersen et al. (2002)].

The objective of our paper is to investigate the conditional mean and volatility interdependencies among major international equity markets in an intraday setting. As argued by Andersen and Bollerslev (1997), news arrivals and the resolution of their informational impact are intimately related to the dynamics of the return volatility process. Our assertion is that 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 are fewer studies that model dynamic intraday interactions between equity markets using high-frequency data. Engle and Susmel (1994) examine the relationship between the New York and London stock markets using concurrent hourly returns. They do not find any significant evidence of volatility spillovers between both markets. Jeong (1999) uses overlapping high-frequency data (5-minute returns during 2 hours of overlapping trading) to explore the transmission pattern of intraday volatility among U.S., Canada and the U.K. His results show that there exists 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.

The analysis of high-frequency data is intriguing in many ways. It has been widely documented that return volatilities vary systematically over the trading day. The pronounced periodic structure in the return volatility has a strong impact on the dynamic properties of high frequency returns. Andersen and Bollerslev (1997) show that standard time series methods applied to high frequency returns may give rise to erroneous inference about the return volatility dynamics. We illustrate the existence of pronounced intraday patterns in average volatility over the trading day across the stock markets. We further demonstrate that correcting for the pronounced period pattern appears critical in examining lead-lag relations between equity markets that trade simultaneously. Our main findings are as follows: First, the New York Stock Exchange (NYSE) typically affects the diurnal pattern in two major European markets. This potential effect of the U.S market's opening points to constant volatility shift and a significant rise in correlations structure within European markets. Second, there are significant and reciprocal intraday spillovers across two European equity markets. Finally, modeling the U.S for the overlapping trading hours with European counterparts yields strong evidence of significant information spillover from U.S to Europe and vice versa.

This paper differs from the existing literature in mainly two aspects. First, it 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, we explicitly model the U.S effect using S&P 500 and thus controlling for overlapping impact on European markets.

The rest of the paper is organized as follows. Section two describes the data; some stylized facts of intraday data are presented in section three. Section four presents multivariate descriptive, and section five outlines the methodology. The empirical findings are reported in section six and section seven summarizes the paper.

2. Data

Our primary dataset consists of 5-minute price quotes on three major equity indices from September 1, 2000 through August 29, 2003, totally three years.[2] The indices are XDAX of Germany, FT100 of UK, and S&P500 of USA. The two European markets share the same opening time, i.e. 9.00

[2] The data were obtained from Olsen Data, Switzerland.

CET[3], whereas the closing time varies. 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, having at least two hours of concurrent trading with the European counterparts. After filtering the data for outliers and other anomalies, more specifically September 11 effect and observations influenced by brief lapses in Reuters data feed, the continuously compounded returns are calculated as $R_{i,t} = 100\times\log(P_{i,t}/P_{i,t-1})$, where $R_{i,t}$ and $P_{i,t}$, represents return and price level on index i at time t respectively. Very occasionally, linear interpolation was used to replace solitary 5-minute price quotes. Finally, the total number of observations summed up to 56160 (702 days) for SP500 stock index, 73851 (717 days) for FT100 stock index, and 99225 (735 days) for XDAX.

2.1 Stylized facts of high frequency data

The usage of high frequency data is interesting and persuasive since it can reveal new information not able to be seen in lower data aggregations, though it poses new challenges. The analysis of these data are complicated by irregular temporal spacing, price discreteness, diurnal pattern and complex, long-lived dependence [Engle and Russel (2002)]. By irregular temporal spacing, we mean that data is inherently irregularly spaced in time. Some transactions occur only seconds apart while others may be far apart. Naturally, this also concerns the pricing of a stock index, though it is a weighted average of a specific number of individual stocks. Discreteness refers to the fact that price changes must fall on multiples of the smallest allowable price change called a tick. With diurnal or periodic pattern we refer to a stylized fact that most stock markets exhibit a U-shaped pattern of volatility. Among the first to document this diurnal pattern were Wood and McInish (1985) and Harris (1986a). Typically, volatility is higher near the open and close of the day whereas the duration or time between trades tends to be shorter near the open and just prior to the close [Engle and Russel (1998)].

[3] Hereafter all trading times are given in Central European Time, CET.

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. Though the 5-minute mean return was practically zero for all markets and dwarfed by its standard deviation, the opposite is true for minimum and maximum return. If pure geometric Brownian motion would be the underlying return generating process, we would expect the minimums and maximums to diminish in size, as the frequencies get higher.

Table 1. Summary Statistics for 5-minute stock index returns

	FT100	XDAX	SP500
Mean	-0.00037	-0.000733	-0.000727
Maximum	3.65	4.68	3.51
Minimum	-3.74	-7.271	-5.136
Std dev.	0.12	0.17	0.14
Skewness	-0.439	-0.549	-0.828
Kurtosis	68.8	58.78	71.25
AC(1)	0.05	0.01	0.07
Percentage of zero returns	1.17	0.9	2.3
No. of observations	73851	99225	56160

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), is slightly positive for all markets, implying some evidence of stale prices.

The intraday seasonalities in average absolute returns are depicted in Figure 1. The calendar effects are obvious in all three markets, while another noticeable feature in Figure 1 is the apparent co-movement of these equity markets. Furthermore, in line with Andersen and Bollerslev (1997), we analyze the autocorrelation pattern of absolute average returns. The autocorrelations for the absolute returns are depicted in Figure 2. For each series the correlogram is lagged for 20 trading days. This operation reveals an intriguing intraday dependence. The high autocorrelations are clustered around the opening and closing of each trading day, except for XDAX that displays a pattern resembling a W. The source for this characteristic is the intraday seasonal volatility pattern depicted in Figure 1, i.e. high volatilities at the opening and closing of the trading day cause the autocorrelation pattern to behave in a cyclical manner. The 20-days correlogram illustrates also the well-known volatility persistence. These distinct systematic fluctuations provide 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 can not accommodate strong regular cyclical patterns”. To avoid potential biases further in the study, we endeavor to eliminate this seasonal component from the returns. The next section introduces the routine of deseasonalizing intraday returns.

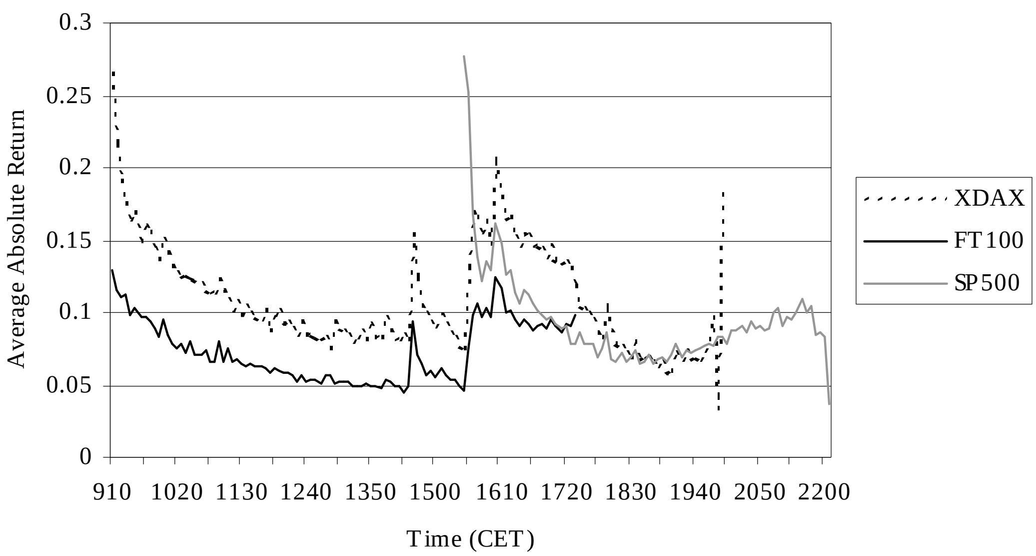

Figure 1. Periodic pattern in intraday volatilities.

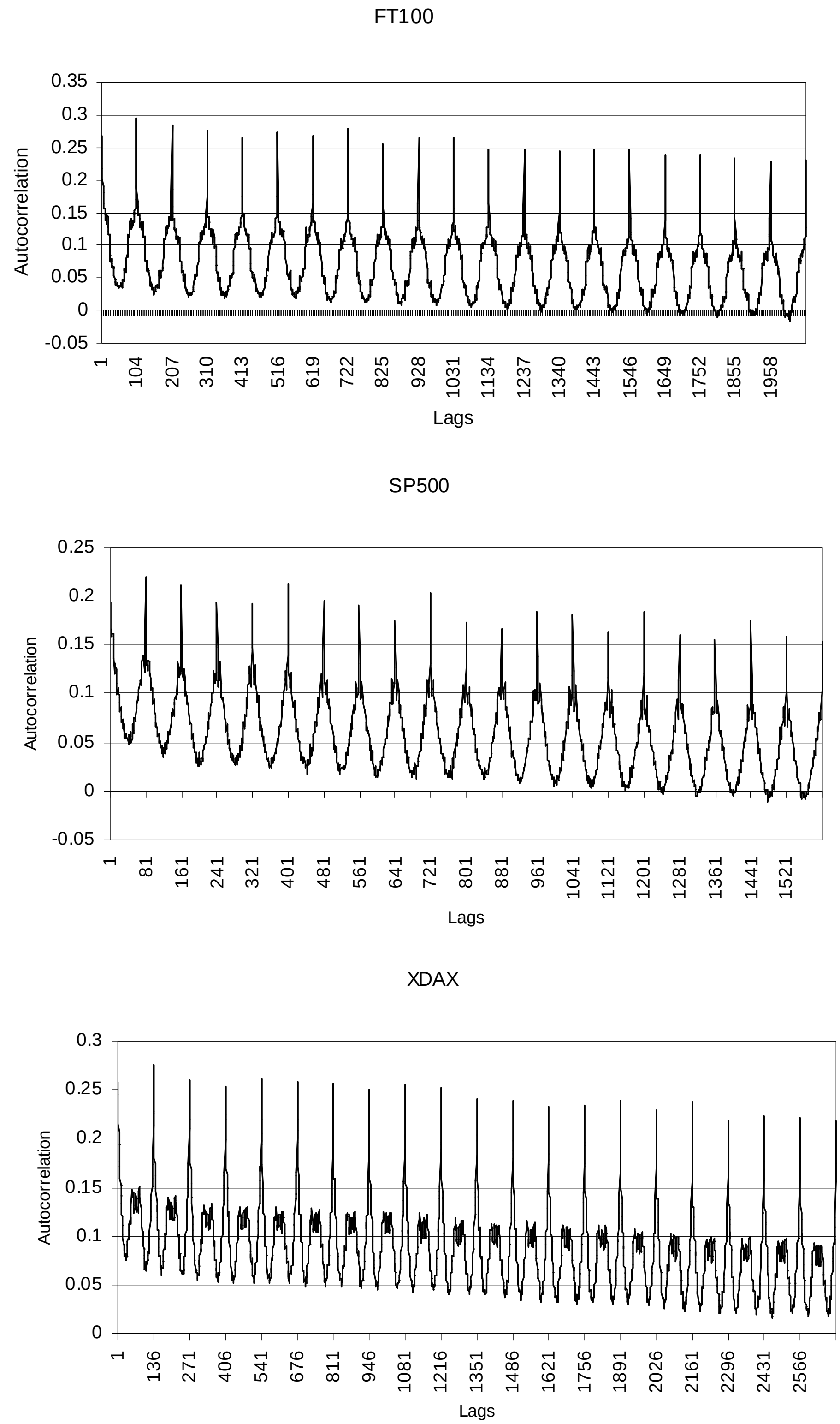

Figure 2. Autocorrelation pattern of five-minute absolute returns for FT100, SP500 and XDAX

Notes: The lag length for all markets is 20 trading days. FT100 has 103 five-minute periods per day, amounting to 2060 lags. SP500 has 80 five-minute periods per day and XDAX 135, amounting to 1600 and 2700 lags, respectively.

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 are so distinctive that there is 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), we consider the following decomposition of the intraday returns[4],

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

where $E\left(R_{t,n}\right)$ is the expected five-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

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

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

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

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

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

Where $N_1 = (N+1)/2$, and $N_2 = (N+1)(N+2)/6$ are normalizing constants. Our model for equity market returns sets $j = 1$, and $p = 2$ based on the Schwartz criterion. 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 $I_{t,n}$, we use major U.S macro economic news announcements that reflect higher volatility in European equity markets. Furthermore, we generally include three time specific dummy variables to minimize the distortion that may otherwise arise from the distinct volatility periods shown in Figure 1. The intraday seasonal volatility pattern is then determined by using

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

The deseasonalized intraday returns are then obtained simply by $\tilde{R}_{t,n} \equiv R_{t,n} \big/ \hat{s}_{t,n}$, while the standardized intraday returns are 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 $S_{t,n}$ in equation 6 is depicted in Figure 3. Clearly, the Flexible Fourier Form representation provides an excellent overall characterization of the intraday periodicity. The correlograms of deseasonalized absolute returns are presented in Figure 4 and confirms that the FFF has reduced the cyclical behavior considerably though the very long-lived persistence becomes perhaps even more apparent.

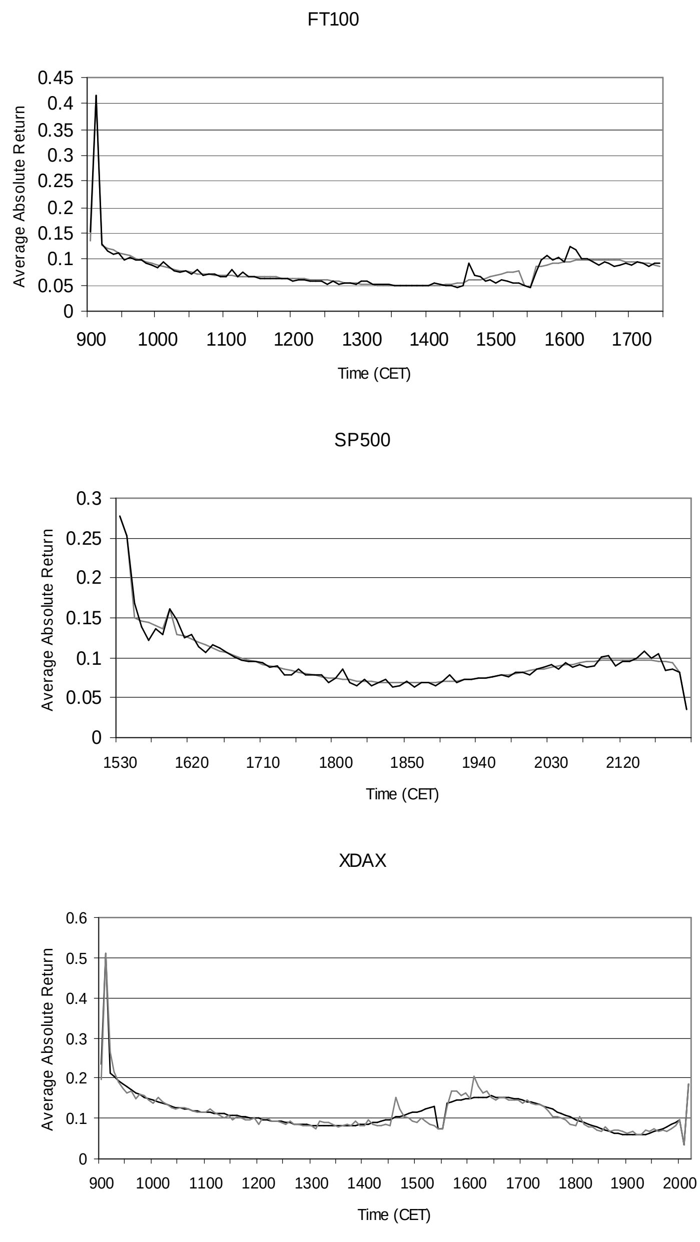

Figure 3. Actual and fitted intraday volatility pattern

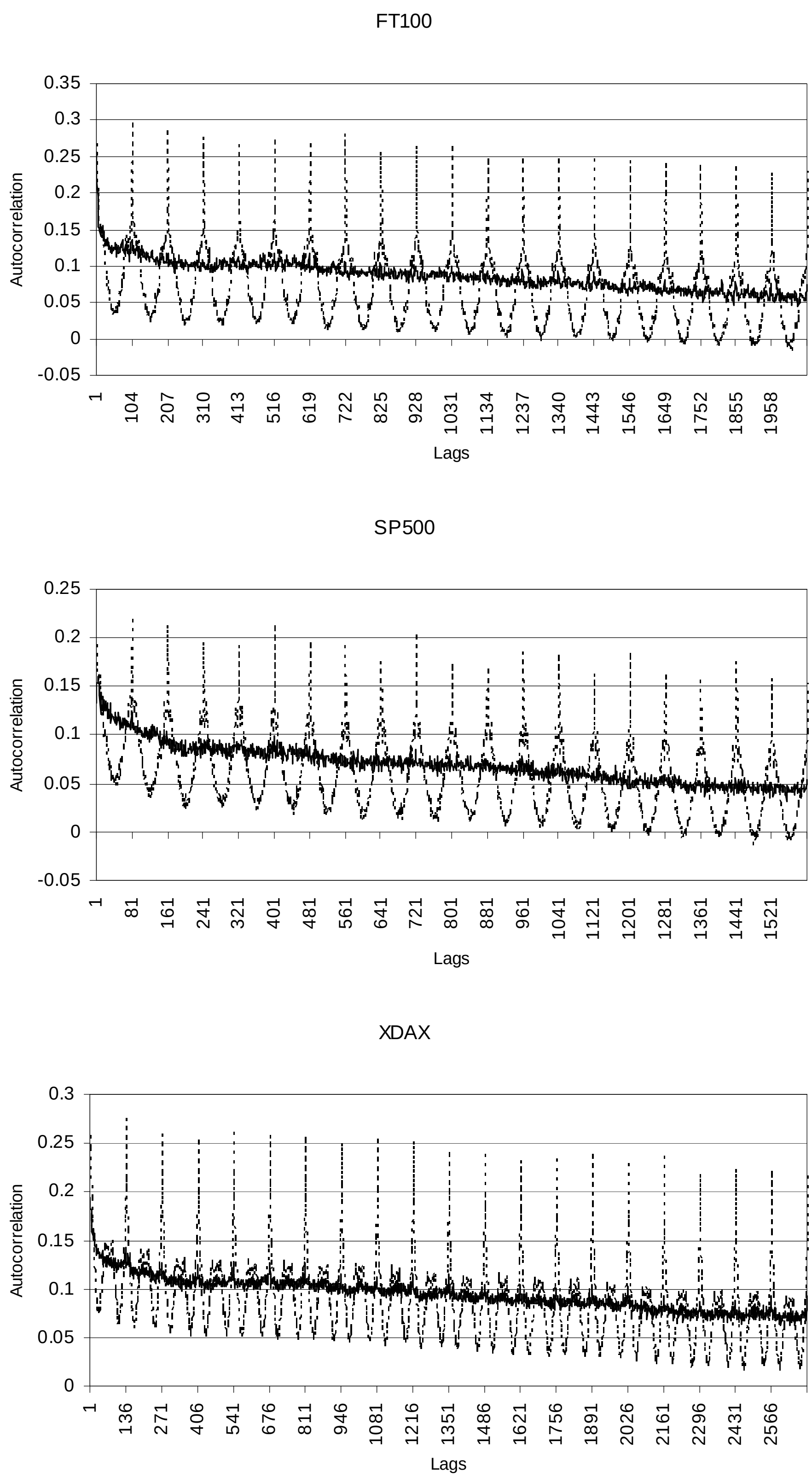

Figure 4. Autocorrelation structure of the deseasonalized returns.

Notes: Solid line presents the absolute average deseasonalized returns and the dashed line the raw returns.

4. Stock market correlations

Once the diurnal pattern has been filtered from the returns, all observations are combined to obtain contemporaneous 5-minute deseasonalized returns. Prior to modeling the first and second moment dependencies we explore the data using simple measures to facilitate additional understanding. Table 3 provides a matrix of contemporaneous and lagged correlations between the three markets. To capture the potential impact of US presence or absence on European stock markets, we divide the trading day in 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 five-minute return correlation between FT100 and XDAX is 0.54 in the first sub-sample. In the second sample the correlation rise to 0.7. To test whether we have a significant break in the linear dependence structure we run restricted least squares, using time sorted returns, on the model

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

The breakpoint was set at 15.35 CET. The F-value of the Chows breakpoint test was 108.96 giving formal support for the suggestion that on average there is an increasing linear return dependence between FT100 and XDAX after 15.30 CET. Both the increased return dependence and the sudden rise in European volatilities occurring exactly at 15.35 would suggest an appearance of a common factor. Building on the notion that the U.S. market is 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, causes the structural break in European equity markets. The cross-autocorrelations show that the XDAX seem to predict more of FT100 returns than vice versa. This relationship seems to be unaffected by the change in the sub-sample.

Table 3. Cross-correlogram of deseasonalized returns

(a) Before 15.30 CET

	FT100	XDAX	SP500
FT100	1		
XDAX	0.54	1	
FT100(-1)	0.05	0.05	-
XDAX(-1)	0.16	0.00	-

(b) from 15:30 to 17.30 CET

	FT100	XDAX	SP500
FT100	1		
XDAX	0.7	1	
SP500	0.60	0.65	1
FT100 (-1)	0.04	-0.02	0.06
XDAX (-1)	0.13	-0.05	0.09
SP500 (-1)	0.08	-0.02	0.06

5. Research methodology

Simultaneous effects of price and volatility spillovers can be estimated by the vector autoregressive-exponential GARCH (VAR-EGARCH) model. Let $R_{i,t}$, i = 1,…,n (i.e., 1 = UK, 2 = Germany, 3 = U.S) be the return for the market i at time t, where the return is calculated as $R_{i,t} = 100 \times \ln (P_{i,t} / P_{i,t-1})$ and $P_{i,t}$ is the stock price of index i at time t. $\varepsilon_{i,t}$ represents the error term conditional on the past information set ψ_{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. The correlation in (11) is assumed to be time-invariant, an assumption that reduces the number of parameters to be estimated. Σ_t is the conditional 2 × 2 variance-covariance matrix . A VAR-EGARCH model depicting price and volatility spillovers may then be formulated as:

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

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

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

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

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 is modeled by equation (10) and is 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 δ_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≠j. A significant $\alpha_{i,j}$ implies volatility spillovers. If the δ_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.

6. Empirical Findings

The maximum likelihood estimates of the bivariate Var-Egarch model are reported separately for different sub-samples in Table 4 panel (a) and (b). The bivariate model considers 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 4 indicate significant return spillovers in both

Table 4. Maximum likelihood estimates of the VAR-EGARCH

	UK		***Germany***
(a) Maximum Likelihood Estimates of bivariate VAR-EGARCH			
$\beta_{1,0}$	0.0001 (1.1344)	$\beta_{2,0}$	0.0001 (0.5058)
$\beta_{1,1}$	-0.0191 (-4.2807)*	$\beta_{2,1}$	0.0510 (9.6395)*
$\beta_{1,2}$	0.1356 (36.8427)*	$\beta_{2,2}$	-0.0473 (-10.4193)*
$\alpha_{1,0}$	-0.1113 (-16.8978)*	$\alpha_{2,0}$	-0.0736 (-16.0938)*
$\alpha_{1,1}$	0.1083 (27.4936)*	$\alpha_{2,1}$	0.0493 (14.6820)*
$\alpha_{1,2}$	0.0421 (11.0494)*	$\alpha_{2,2}$	0.0715 (19.8290)*
δ_1	-0.0559 (-2.5674)*	δ_2	-0.1920 (-5.9357)*
γ_1	0.9836 (1084.9264)*	γ_2	0.9884 (1476.0690)*
$\rho_{1,2}$	0.5062 (134.2999)*		

UK-Germany (Market1,2)		***UK-U.S (Market1,3)***		***Germany-U.S (Market2,3)***	
(b) Maximum Likelihood Estimates of bivariate VAR-EGARCH					
$\beta_{1,1}$	-0.0881 (-9.3654)*	$\beta_{1,1}$	-0.0400 (-4.880)*	$\beta_{2,2}$	-0.0614 (-6.3973)*
$\beta_{2,2}$	-0.0502 (-5.0309)*	$\beta_{3,3}$	0.0336 (3.7052)*	$\beta_{3,3}$	0.0012 (0.1307)
$\beta_{1,2}$	0.1510 (20.5836)*	$\beta_{1,3}$	0.0932 (14.2973)*	$\beta_{2,3}$	0.0164 (1.9012)
$\beta_{2,1}$	0.0132 (1.1072)	$\beta_{3,1}$	0.0092 (0.8241)	$\beta_{3,2}$	0.0409 (4.3075)*
$\alpha_{1,1}$	0.0994 (22.6769)*	$\alpha_{1,1}$	0.0810 (13.4654)*	$\alpha_{2,2}$	0.0885 (14.2503)*
$\alpha_{2,2}$	0.1290 (44.3367)*	$\alpha_{3,3}$	0.0525 (9.2935)*	$\alpha_{3,3}$	0.0494 (9.2663)*
$\alpha_{1,2}$	0.0599 (16.1660)*	$\alpha_{1,3}$	0.0103 (2.0045)*	$\alpha_{3,2}$	0.0171 (3.0868)*
$\alpha_{2,1}$	0.0393 (9.3508)*	$\alpha_{3,1}$	0.0308 (5.6262)*	$\alpha_{2,3}$	0.0408 (7.3648)*
$\delta_{1,2}$	-0.1196 (-4.5711)*	$\delta_{1,3}$	-0.1301 (-2.9328)*	$\delta_{2,3}$	-0.1162 (-3.1110)*
$\delta_{2,1}$	-0.1002 (-5.8541)*	$\delta_{3,1}$	-0.2649 (-4.3949)*	$\delta_{3,2}$	-0.2090 (-3.8611)*
γ_1	0.9815 (1011.0073)*	γ_1	0.9935 (1189.2928)*	γ_2	0.9965 (1825.9636)*
γ_2	0.9810 (993.8371)*	γ_3	0.9920 (941.5359)*	γ_3	0.9957 (1493.7779)*
$\rho_{1,2}$	0.6866 (199.9503)*	$\rho_{1,3}$	0.6423 (117.8522)*	$\rho_{2,3}$	0.7481 (182.5395)*

(a) The maximum likelihood estimates are obtained using bivariate VAR-EGARCH for UK and Germany for concurrent trading hours between 0900 and 1530 (CET) for the period September 1, 2000 through August 1, 2003. The estimation is done assuming multivariate t distribution with 5 degrees of freedom. Numbers in parenthesis are t-statistics for estimated coefficients. * Denotes significance at 5% level.
(b) The maximum likelihood estimates are obtained using bivariate VAR-EGARCH for UK, Germany and U.S for concurrent trading hours between 1530 and 1730 (CET) for the period September 1, 2000 through August 1, 2003. The estimation is done assuming multivariate t distribution with 5 degrees of freedom. Numbers in parenthesis are t-statistics for estimated coefficients. * Denotes significance at 5% level. The constant terms are omitted here for convenience, however, may be obtained from authors upon request.

directions, i.e., from Germany to UK, $\beta_{1,2}$ = 0.1356 suggesting that roughly 13 % of the German returns innovation is transferred to the British stock market whereas the only 5% of the British return innovation is on average spilled over to the German market. The return correlation was 0.5 slightly less than the contemporaneous presented in table 3. Concerning the second moment interdependencies, in addition to own past innovations (arch-effects), the volatility spillovers are also clearly seen in both directions. Thus the conditional variance in each market is affected by innovations coming from other market. In line with earlier findings [e.g., Kuotmos (1996) and Kanas (1998)], the volatility transmission mechanism is asymmetric in both markets, confirming that both the size and the sign of the innovations are important determinants of the volatility transmission mechanism. Another interesting finding is the degree of volatility persistence; the γ coefficient is highly persistent in both markets, indicating a very long or nearly integrated memory process. This finding has been discussed widely [Andersen and Bollerslev(1997)] in financial literature using high frequency data that points to a slow hyperbolic rate of decay in the autocorrelation structure of the absolute returns, which is consistent with the presence of long-memory features in the volatility process.

We now turn to the bivariate VAR-EGRACH estimates for two hours of concurrent afternoon trading between UK, Germany and US. In interpreting the results, it is important to recognize that after the opening of the SP500 at 15.30 CET, the correlation between U.K and Germany rises significantly from 0.50 to 0.69. We assert that the opening of NYSE induces greater interdependence between the two major European equity markets. The results presented in the lower panel of the table 4 (b) indicate significant price spillovers from both Germany and the US to the UK, whereas returns in the German equity market are largely unaffected by past returns in any of the two markets. The US market's returns are influenced by the return process in the German equity market, while the UK market does not seem to have any significant influence on US returns.

Focusing on the parameters describing the conditional volatility in each market, it can be seen that the volatility spillovers between two European markets, UK and Germany are significant, virtually unchanged from the upper panel of the table 4a. Furthermore, the volatility spillovers are significant and reciprocal in all instances among all three markets; the UK, Germany and the US. These findings confirm that in addition to their own past innovations, the conditional variance in each market is also affected by innovations originating in other stock markets during the concurrent trading hours. This is also consistent with Jeong (1999), that the volatility spillover is not unidirectional from the U.S to foreign markets. Rather there exists a strong interdependence in the volatility transmission during the overlapping trading hours.

The volatility transmission mechanism is asymmetric in all three markets, confirming that both the size and the sign of the innovations are important determinants of the volatility transmission mechanism. Moreover, these estimates further confirm a high degree of volatility persistence; the γ coefficient is highly persistent in all three markets, indicating a long memory process.

7. Summary

This paper explores the dynamic first and second moment linkages among international equity markets using 5-minute index returns for a three-year period. We split our sample into two sub samples according to time. The first sub sample consists of 5-minute return observations for two major European stock indices of FTSE 100 of UK and XDAX of Germany until 15.30 CET, while the second sub sample between 15.35 and 17.30 (CET) allows us to model intraday dependencies of two major European markets with the U.S.

The diurnal pattern clearly depicts that on average volatilities in the German and British stock market increase significantly at the New York Stock Exchange (NYSE) opening time. Interestingly, the return dependence between Germany and UK is also significantly amplified during the afternoon trading. This suggests that the US market heavily impacts the return and volatility processes on the European markets.

We address this question by modeling the return and volatility dependencies by a multivariate Var-Egarch model. Due to the cyclical autocorrelation structure induced by intraday seasonal volatility, all five-minute returns are deseasonalized using Flexible Fourier form. Our results show a clear association both in returns and volatilities between the UK and Germany. This relationship appears virtually unchanged by the presence or absence of the US market.

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