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Periodic Dynamic Conditional Correlations between Stock Markets in Europe and the US

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Abstract

This study extends the dynamic conditional correlation model to allow day-specific correlations of shocks across international stock markets. The properties of the resulting periodic dynamic conditional correlation (PDCC) model are examined, with the model then applied to study the intra-week interactions between six developed European stock markets and the US over the period 1993 - 2005. We find very strong evidence of periodic effects in the conditional correlations of the shocks. The highest correlations are generally observed on Thursdays, with these Thursday correlations in some cases being twice those on Monday or Tuesday. Prior to estimating the PDCC model, periodic mean and volatility effects are removed using a PAR model for returns combined with a periodic EGARCH specification for the variance equation. Strong periodic mean effects are found for returns in the French, Italian and Spanish stock markets, whereas such effects are present in volatility for all stock markets except Italy.

JEL Classifications: G10; G12; G22.

Keywords: Day-of-the-week-effect, conditional correlations, volatility, periodic models.

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1. Introduction

An important feature of stock market prices is the presence of so-called calendar effects, by which predictable patterns associated with the month of the year, the day of the week or the hour of the day exist in mean returns and/or their volatility. The existence of such predictable patterns does not necessarily imply that the market is irrational, but these patterns nevertheless provide investors and analysts with information about the functioning of the markets and the nature of the shocks to which they are subject.

This paper considers an important, but apparently unstudied, aspect of calendar effects, namely day-of-the-week patterns in the cross-market correlations of returns. In order to focus on this phenomenon, we extend the dynamic conditional correlation (DCC) model of Engle (2002) to allow for day-specific effects. Adopting the usual terminology that refers to models in which parameters change systematically with the calendar as being periodic, we refer to our model as a periodic dynamic conditional correlation, or PDCC, specification. Building on Engle (2002), a number of recent studies have investigated the dynamic behavior of conditional correlations of shocks across various markets (for instance see Cappiello et. al., 2003, van Dijk, Munandar and Hafner, 2005, among others). However, to the best of our knowledge, no study has examined whether these correlations exhibit systematic intra-week patterns.

The existence of day-of-the-week patterns in returns and their volatilities is well established (Abraham and Ikenberg, 1994, Bessembinde and Herzel, 1993, Cross, 1973, French, 1980, Gibbons and Hess, 1981, Keim and Stambaug, 1984, Rogalski, 1984), with Jacops and Levy (1988) explaining the “Monday effect” (by which returns on Mondays are lower than on other days) based on human nature in combination with the tendency to announce good news quickly and to defer bad news. Other studies investigate day-of-the-week effects in volatility; for example, Foster and Viswanathan (1990) demonstrate that Monday volatility tends to be higher than that of other days, while other studies show day-specific effects to be pervasive for the parameters of the volatility equations (Bollerslev and Ghysels, 1996, Bubak and Zikes, 2006, Fantazzini and Rossi, 2005, Franses and Paap 2000).

The factors causing intra-week patterns in returns or volatility may also apply to cross-market correlations. For example, if “bad news” is announced over the weekend, leading to lower Monday returns and higher volatility, then Monday shock correlations across markets may also be higher than other days, due to the observed feature that markets are more strongly correlated during declines than during bull runs (Cappiello, Engle and Sheppard, 2003, Longin and Solnik, 2002, Ang and Bekaert, 2002, among others). However, the literature on day-of-the-week effects has examined only single markets in isolation, and hence cannot shed any light on whether cross-market relationships display any intra-week patterns. Our study focuses on the presence (or otherwise) of such effects in relation to daily closing prices for six developed stock markets, namely those of the US, UK, Germany, France, Spain, Italy and Switzerland over the period January 1993 to April 2005.

Prior to employing the PDCC model, we employ a periodic autoregressive (PAR) mean equation combined with a periodic generalized exponential autoregressive conditional heteroscedasticity (PEGARCH) volatility model for daily stock market returns. Conditioning on these, the estimated PDCC model for the shocks allows all parameters to be day-specific.

Although our results generally confirm those of previous studies in relation to the presence of periodic effects in the mean and (more especially) the volatility equations, we find much stronger evidence that the conditional correlations across markets exhibit day-specific patterns. Therefore, we believe that periodic effects in stock markets are driven primarily by the nature of the shocks, whose periodic correlations may be due to systematic patterns in the days on which important macroeconomic data are released.

The remainder of this paper is structured as follows. Our PDCC model is described in Section 2, where its properties are also examined. Section 3 then outlines the methodology we use in our empirical application, while Section 4 presents the data and describes its properties in relation to intra-week patters. Empirical results are presented in Section 5, which includes the results of hypothesis tests that examine the nature of periodic effects. Finally, Section 6 concludes.

2. The Periodic Dynamic Conditional Correlation Model

The Dynamic Conditional Correlation (DCC) model of Engle (2002) provides an attractive framework for modeling the changing nature of correlations between financial time series, because it captures changing correlations of shocks while being relatively parsimonious[1]. This section extends the DCC model to consider day of the week effects, and examines key properties of the resulting periodic DCC (PDCC) specification.

2.1 Periodic conditional correlations

We start with the multivariate $n\times1$ stochastic process $\{\varepsilon_t\}$ such that

$$\varepsilon_t | \Omega_{t-1} \sim (0, \Sigma_t) \qquad (1)$$

where $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2,t}, ..., \varepsilon_{nt}]'$ and Ω_{t-1} denotes all information available at time t-1; we will later associate ε_{it} with the shock relating to market i for day t. The time-varying matrix of conditional covariances in (1) can be written

$$\Sigma_t = S_t R_t S_t, \qquad (2)$$

[1] See also Tse and Tsui (2002), who propose a similar model.

where $S_t = diag(\sqrt{h_{1t}}, \sqrt{h_{2t}}, ..., \sqrt{h_{nt}})$ is the vector of conditional standard deviations, with $h_{it} = E[\varepsilon_{it}^2 | \xi_{t-1}]$. Finally, R_t is the time-varying symmetric conditional correlation matrix with $(i, j)^{th}$ element $\rho_{ij,t}$ and

$$\rho_{ij,t} = E[\upsilon_{it}\ \upsilon_{jt} | \Omega_{t-1}], \qquad i,\ j = 1, 2, ..., n. \tag{3}$$

where $\upsilon_{it} = \varepsilon_{it} / \sqrt{h_{it}}$ is the standardized for market i at time t.

The PDCC model represents the dynamics of $\rho_{ij,t}$, allowing these to exhibit systematic intra-week patterns. In particular, generalizing the DCC model of Engle (2002), the dynamics of the conditional correlations are specified through

$$Q_t = \sum_{s=1}^{5} [C_s + A_s \upsilon_{t-1} \upsilon_{t-1}' A_s + B_s Q_{t-1} B_s] D_{st} \tag{4}$$

in which C_s is a $n \times n$ matrix of constants, while A_s and B_s are $n \times n$ diagonal matrices that account for the short and long run persistency, respectively, in the conditional correlation dynamics for each pair of markets and $\upsilon_t = (\upsilon_{1t},\ \upsilon_{2t},\ \ldots,\ \upsilon_{nt})'$. The scalar variable D_{st} in (4) is a dummy variable for day s, which is unity when t falls on day s (s = 1, 2, 3, 4, 5) and zero otherwise.

Since Q_t in (4) does not satisfy the requirement that a correlation matrix have unit diagonal elements, this is imposed by defining

$$R_t = (Q_t^*)^{-1}\, Q_t\, (Q_t^*)^{-1} \tag{5}$$

where Q_t^* is a diagonal matrix with $q_{ii,t}^* = \sqrt{q_{ii,t}}$ and lower case letters indicate the appropriate elements of the corresponding matrices. For R_t to be positive definite we require only that Q_t is positive definite. As in Cappiello, Engle and Sheppard (2003), Q_t is positive definite with probability one if C_s (s = 1, …., 5) is positive definite, and we return to this in the next subsection.

2.2 Properties of the PDCC model

Since A_s and B_s are diagonal, (4) can be written in scalar form (and in an obvious notation in relation to (4)) as

$$q_{ij,t} = \sum_{s=1}^{5} [c_{ij,s} + \mathrm{a}_{ii,s}\mathrm{a}_{jj,s}\upsilon_{i,t-1}\upsilon_{j,t-1} + b_{ii,s}b_{jj,s}q_{ij,t-1}]D_{st} \,. \qquad (6)$$

Defining $\psi_{ij,t} = \upsilon_{it}\upsilon_{jt}$ and $\eta_{ij,t} = \psi_{ij,t} - q_{ij,t}$, this has the ARMA representation

$$\psi_{ij,t} = \sum_{s=1}^{5} [c_{ij,s} + (\mathrm{a}_{ii,s}\mathrm{a}_{jj,s} + b_{ii,s}b_{jj,s})\psi_{ij,t-1} - b_{ii,s}b_{jj,s}\eta_{ij,t-1}]D_{st} + \eta_{ij,t} \,. \qquad (7)$$

For i, j = 1, …, n ($i \neq j$), define the vectors $\Psi_{ij,w} = \left(\psi_{ij,5(w-1)+1,}, \psi_{ij,5(w-1)+2,}, ..., \psi_{ij,5(w-1)+5}\right)'$ and $N_{ij,w} = \left(\eta_{ij,5(w-1)+1,}, \eta_{ij,5(w-1)+2,}, ..., \eta_{ij,5(w-1)+5}\right)'$ that collate the elements relating to week w. Then the vector representation of (7) is (for analogous cases see Tiao and Grupe, 1988, or Osborn, 1991)[2]

$$\Lambda_{ij,0}\Psi_{ij,w} = C_{ij} + \Lambda_{ij,1}\Psi_{ij,w-1} + \mathrm{M}_{ij,0}N_{ij,w} + \mathrm{M}_{ij,1}N_{ij,w-1} \qquad (8)$$

where $C_{ij} = \left(c_{ij1}, c_{ij,2}, c_{ij,3}, c_{ij,4}, c_{ij,5}\right)'$, the autoregressive matrices are defined as

$$\Lambda_{ij,0} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ -\lambda_{ij,2} & 1 & 0 & 0 & 0 \\ 0 & -\lambda_{ij,3} & 1 & 0 & 0 \\ 0 & 0 & -\lambda_{ij,4} & 1 & 0 \\ 0 & 0 & 0 & -\lambda_{ij,5} & 1 \end{pmatrix}, \; \Lambda_{ij,1} = \begin{pmatrix} 0 & 0 & 0 & 0 & \lambda_{ij,1} \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}, \qquad (9)$$

where $\lambda_{ij,s} = a_{ii,s}a_{jj,s} + b_{ii,s}b_{jj,s},$ while $M_{ij,0}$, $M_{ij,1}$ have the same form as $\Lambda_{ij,0}$ and $\Lambda_{ij,1}$ respectively, with the elements $\lambda_{ij,s}$ replaced by $b_{ii,s}b_{jj,s}$ (s = 1, 2, 3, 4, 5).

From (8), the existence of the stationary mean $E[\Psi_{ij,w}]$, which is the correlation of (standardized) shocks between markets i and j for week w, requires the roots of the characteristic

[2] For simplicity of notation, we assume that the first observation relates to the first day of the week (Monday). Also for notational simplicity, we assume that T/5 is integer and hence w = 1, 2, …, T/5, where T is the total number of daily observations available.

equation $\left|\Lambda_{ij,0} - \Lambda_{ij,1}z\right| = (1 - \lambda_{ij,1}\lambda_{ij,2}\lambda_{ij,3}\lambda_{ij,4}\lambda_{ij,5}z) = 0$ to lie outside the unit circle. This condition is analogous to that required for the stationarity of periodic autoregressive processes; see Tiao and Grupe (1988) or Osborn (1991). Applied to all pairs, the PDCC model is therefore stationary, if

$$\prod_{s=1}^{5}\lambda_{ij,s} = \prod_{s=1}^{5}(\mathrm{a}_{ii,s}\mathrm{a}_{jj,s} + b_{ii,s}b_{jj,s}) < 1, \quad \text{all } i,\ j, = 1, 2, \ldots, n;\ i \neq j\,. \tag{10}$$

Assuming the existence of the stationary mean, it is easy to see that (8) implies that the unconditional weekly correlation shock matrix satisfies

$$E[\Psi_{ij,w}] = (\Lambda_{ij,0} - \Lambda_{ij,1})^{-1}C_{ij}, \tag{11}$$

and hence a natural consequence of the periodic specification is that distinct unconditional correlations of the normalized shocks υ_{it}, υ_{jt} can apply for the different days of the week.

An alternative representation of (11) is obtained by noting that because $\upsilon_t\upsilon_t' - Q_t$ has mean zero, (4) implies, assuming stationarity in mean for all i , j = 1, 2, …., n ($i \neq j$), that

$$E[\upsilon_t\,\upsilon_t'] = \sum_{s=1}^{5}\{C_s + A_s E[\upsilon_{t-1}\upsilon_{t-1}']A_s + B_s E[\upsilon_{t-1}\upsilon_{t-1}']B_s\}\, D_{st}\,. \tag{12}$$

Note that the $(i,\ j)^{\text{th}}$ element of $E[\upsilon_t\upsilon_t']$ is equal to the s^{th} element of $E[\Psi_{ij,w}]$ in (11) when t corresponds to day s of the week. Writing $E[\upsilon_t\upsilon_t'] = \overline{Q}_s$ for day s, it follows from (12) that

$$C_s = \overline{Q}_s - A_s\overline{Q}_{s-1}A_s - B_s\overline{Q}_{s-1}B_s\,. \tag{13}$$

Indeed, Engle (2002) specifies the DCC model using a nonperiodic version of (13), with $\overline{Q}_s = \overline{Q}_{s-1} = \overline{Q}$, $A_s = A$ and $B_s = B$ (s = 1, …, 5), rather than with an unrestricted matrix of constants C. In our context, (10) provides the conditions for the validity of the periodic generalization (13) and, assuming these are satisfied, our estimated PDCC model is based on using (13) to substitute for C_s in (4).

3. Methodology

This outline of the methodology used in our empirical application of the PDCC model begins with the specification of the mean and volatility equations that are estimated prior to the PDCC specification. The section also discusses the hypothesis tests of interest and estimation issues.

3. 1 Mean and volatility equations

To ensure that unmodelled periodic mean and volatility effects do not distort inferences from the PDCC specification, we employ a PAR-PEGARCH model for returns. The PAR specification for the means allows the autoregressive parameters to vary with the day of the week, while the PEGARCH specification does the same for the volatility. The PAR-PEGARCH model is employed separately for each market, with the mean and volatility equations estimated jointly.

Denoting an individual stock market index at time *t* by P_t, the PAR(*p*)-PEGARCH(1,1) model for the continuously compounded stock returns $y_t = 100*[\ln(P_t) - \ln(P_{t-1})]$, is given by

$$y_t = \sum_{s=1}^{5}\left(a_s + \sum\nolimits_{i=1}^{p} \phi_{is} y_{t-i}\right) D_{s,t} + \varepsilon_t \qquad (14)$$

$$\varepsilon_t = \upsilon_t \sqrt{h_t}, \quad \upsilon_t \sim iid(0,1) \qquad (15)$$

$$h_t = \sum_{s=1}^{5} (\exp\left[\omega_s + \gamma_s \upsilon_{t-1} + \theta_s \left(|\,\upsilon_{t-1}\,| - E\,|\,\upsilon_{t-1}\,|\right) + \delta_s \ln h_{t-1}\right]) D_{s,t} \qquad (16)$$

Note that all parameters in (14) and (16), namely α_s, φ_s, ω_s, γ_s, θ_s and δ_s, are allowed to be day-specific. Our estimated models employ a PAR(1) in (14) since the AIC and SIC criteria are in favour of this specification[3]. The EGARCH volatility specification of Nelson (1991) is adopted in (16) to ensure that all implied volatilities are positive and to allow the possibility of asymmetry, so that negative shocks may have a different effect on volatility than positive ones. First order

[3] Models with AR orders 1 and 5 were used in estimations to capture any possible weekly patterns in the data. However, the coefficients of the 5th order were insignificant and AR(1) models were preferred by AIC and SIC.

dynamics are used in (16) since this is widely found to adequately capture volatility dynamics. Here day-specific volatility persistence is measured by δ_s, the magnitude effect is captured by θ_s while asymmetry in volatility typically implies negative γ_s. In contrast to previous studies that employ periodic GARCH models (Bollerslev and Ghysels, 1996, Franses and Paap, 2000, Fantazzini and Rossi, 2005, among others), we allow the persistence parameter δ to vary over the days of the week and employ an EGARCH specification to ensure positive implied variances.

The stationarity conditions for the mean process of equation (14) are well known and are discussed by, among others, Tiao and Grupe (1980), Osborn (1991), Franses and Paap (2000) or Ghysels and Osborn (2001, pp.144-146). Assuming stationarity, and in an analogous way to (11), a natural consequence of the PAR specification for daily returns is that distinct underlying means can apply for the different days of the week.

Since, to our knowledge, a PEGARCH model has not been employed in previous empirical applications, it is useful to examine the conditions for the existence of constant unconditional mean volatility. Employing a similar analysis to the PDCC model above, consider the PEGARCH volatility process of (16) and define the log conditional volatility vector for week w as H_w = $[ln(h_{5(w-1)+1}), ln(h_{5(w-1)+2}), \ldots, ln(h_{5(w-1)+5})]'$ so that in a similar way to (8), the PEGARCH model (16) can be written as

$$\Delta_0 H_w = \omega + \Delta_1 H_{w-1} + V_w \qquad (17)$$

where the 5 × 5 matrices Δ_0 and Δ_1 are defined in terms of $\delta_1, \ldots, \delta_5$ analogously to the definitions of Λ_0, Λ_1 in (9), simply replacing $\lambda_{ij,s}$ by δ_s, while $\omega = (\omega_1, \omega_2, \ldots, \omega_5)'$ and the 5 × 1 vector V_w has s^{th} element $\gamma_s \upsilon_{5(w-1)+s-1} + \theta_s(|\upsilon_{5(w-1)+s-1}| - E|\upsilon_{5(w-1)+s-1}|)$. Generalising the nonperiodic analysis of Nelson (1991) to the VAR(1) of (17), the PEGARCH process has a constant unconditional mean provided $|\delta_1\delta_2\delta_3\delta_4\delta_5| < 1$ and is integrated if this product is unity.

Under the condition $|\delta_1\delta_2\delta_3\delta_4\delta_5| < 1$ and by taking expectations, (17) yields

$$E[H_w] = (\Delta_0 - \Delta_1)^{-1}\omega \tag{18}$$

so that the PEGARCH model allows expected log conditional volatility to be day-specific[4]. This day-specific effect may arise through periodic variation in the intercepts ω_s and/or the persistence coefficients δ_s of (16).

3.2 Hypotheses of interest

Previous literature finds evidence of periodic effects in daily stock market returns and their volatility (Keim and Stambaug, 1984, Bessembinde and Herzel, 1993, Bollerslev and Ghysels, 1996, Franses and Paap, 2000, among others). To investigate whether these apply also for our PAR(1)-PEGARCH(1,1) models, we consider the following hypotheses:

$$\begin{aligned}
&H_1 : \phi_{is} = \phi_i \quad i = 1, \ldots, p; s = 1, 2, 3, 4, 5 \\
&H_2 : \phi_{is} = \phi_i, \alpha_s = \alpha \quad i = 1, \ldots, p; s = 1, 2, 3, 4, 5 \\
&H_3 : \omega_s = \omega \quad s = 1, 2, 3, 4, 5 \\
&H_4 : \delta_s = \delta \quad s = 1, 2, 3, 4, 5 \\
&H_5 : \omega_s = \omega, \theta_s = \theta, \gamma_s = \gamma, \delta_s = \delta \quad s = 1, 2, 3, 4, 5
\end{aligned}$$

The first two hypotheses consider the need for a periodic specification for the mean equation, while H_3 to H_5 examine periodicity in the EGARCH model. In particular, H_3 examines whether the intercept has a periodic form, while H_4 considers whether volatility persistence is day specific and H_5 is the overall test for a nonperiodic EGARCH. In addition, we consider the null hypothesis of an integrated PEGARCH process, namely

$$H_6 : \prod_{s=1}^{5} \delta_s = 1$$

[4] The properties of unconditional volatility are complex in a EGARCH model; see, for example, the expressions of Karanasos and Kim (2003) for the moments of ε_t^2 in a non-periodic EGARCH specification.

However, our principal interest centres on the PDCC model, and four hypotheses are examined to establish the nature of any periodic variation in the conditional correlations, namely

$$H_7 : A_s = A \quad (s = 1, 2, 3, 4, 5)$$
$$H_8 : B_s = B \quad (s = 1, 2, 3, 4, 5)$$
$$H_9 : A_s = A, B_s = B \quad (s = 1, 2, 3, 4, 5)$$
$$H_{10} : \mathrm{a}_{jj,s} = \mathrm{a}_s, b_{jj,s} = b_s \quad (j = 1, 2, \ldots, n; s = 1, 2, 3, 4, 5)$$

Therefore, our tests not only examine the overall null hypothesis of no periodic coefficients in (4), which is represented by H_9, but also whether any such periodicity is confined to the parameters capturing short term or long term persistency (H_7 and H_8 respectively). In addition, H_{10} examines whether the PDCC coefficients vary over countries, or whether the same day-specific effects are common across countries.

Finally, we examine the null hypothesis that a periodically integrated PDCC is required for each pair of markets:

$$H_{11} : \prod_{s=1}^{5} (\mathrm{a}_{ii,s}\mathrm{a}_{jj,s} + b_{ii,s}b_{jj,s}) = 1 \quad (i \neq j; i, j = 1, 2, ..., n)$$

3.3 Estimation and inference

Engle and Sheppard (2001) show that the log-likelihood function for a DCC model can be written as the sum of a returns/volatility part and a correlation part. Denoting the parameters of (14) and (16) by the vector ξ and the parameters in the conditional correlation matrix R_t by ζ, and assuming the availability of T sample observations, this result implies for our case that

$$L(\xi, \zeta) = L_v(\xi) + L_c(\xi, \zeta) \qquad (19)$$

with volatility term

$$L_v(\xi) = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log|S_t| + \varepsilon_t' S_t^{-1} S_t^{-1}\varepsilon_t \qquad (20)$$

and correlation component

$$L_c(\xi,\zeta) = -\frac{1}{2}\sum_{t=1}^{T}(-\upsilon_t'\upsilon_t + \log|R_t| + \upsilon_t' R_t^{-1}\upsilon_t). \tag{21}$$

Following Engle (2002), we obtain consistent parameter estimates through a two step procedure, first maximizing the likelihood for the volatility part to find $\hat{\xi} = \arg\max\{L_v(\xi)\}$, from which the residuals $\hat{\varepsilon}_t$ and standardized residuals $\hat{\upsilon}_t = \hat{S}_t^{-1}\hat{\varepsilon}_t$ are obtained. These standardized residuals are then used to estimate ζ as $\hat{\zeta} = \arg\max\{L_c(\hat{\xi},\zeta)\}$. Calculation of standard errors for the estimated DCC parameter vector $\hat{\zeta}$ takes the first step (PAR-PEGARCH estimation) into account, using the method described by Engle and Sheppard (2001).

In order to conserve degrees of freedom in estimation, the intercept matrix C_s of (4) is estimated through (13), replacing $\overline{Q}_s$ by $(T/5)^{-1}\sum_{w=1}^{T/5}\hat{\upsilon}_{5(w-1)+s}\hat{\upsilon}_{5(w-1)+s}'$ which corresponds to day s of the week. As noted in section 2.1 above, positive definiteness of C_s is important for the positive definiteness of Q_t. However, although the sample analogue of $\overline{Q}_s$ is positive definite by construction, this is not sufficient to guarantee that the resulting estimated intercept matrix defined through (13) is necessarily positive definite even when the conditions for stationarity in mean of the PDCC model are satisfied. We adopt the practical solution to this potential problem of checking positive definiteness of C_s during estimation.

Inference related to the null hypothesis of the absence of periodic effects in the PAR-PEGARCH model, H_1 to H_5 in (14)-(16), is conducted via Wald tests, applied to models estimated separately for each market. However, the PDCC model is estimated jointly across all n markets, making computation of the corresponding joint Wald tests complex in relation to H_6 to H_{10}. Therefore, for ease of calculation, these latter hypothesis tests are conducted using likelihood ratio statistics. Finally, the tests of the null hypotheses of integrated PEGARCH and integrated PDCC models, H_6 and H_{11}, respectively, are both computed using Wald statistics.

In all cases, the test statistics are compared to the asymptotic χ^2 distribution, with degrees of freedom given by the number of restrictions. To our knowledge, the distributions of test statistics for integrated EGARCH and integrated DCC specifications have not been formally examined. However, we presume that an asymptotic χ^2 distribution applies these, based on the result of Lumsdaine (1995) for the corresponding test in a GARCH framework.

4. Data

Our stock market data consist of the closing daily prices of S&P500 (USA), DAX-30 (Germany), FTSE-100 (UK), CAC-40 (France), IBEX-35 (Spain) and the total indices of the Italian and Swiss markets[5]. These particular markets were chosen since they account for more than 80% of total stock market capitalization in Europe and four of these countries (Germany, France, Italy and Spain) have adopted the common Euro currency. Further, the US and UK stock markets are home to many of the world's largest companies while Switzerland attracts the interest of international investment due to its political and economic stability and the traditionally high quality of services provided. The first five indices are designed to reflect the largest firms[6], while the total indices

[5] It should be noted that closing prices are non-synchronous across countries (especially between US and European stock markets), which may lead to underestimation of correlations (see Martens and Poon, 2001). However, we choose to use closing data as we believe they best represent daily returns and volatilities for each market.

[6] DAX-30 is a price-weighted index of the 30 most heavily traded stocks in the German market, while FTSE-100 is the senior index in the UK and consists of the largest 100 UK companies by full market value. CAC-40 is calculated on the basis of 40 largest French stocks based on market capitalization on the Paris Bourse. IBEX-35 is composed of the 35 securities quoted on the Joint Stock Exchange System of the four Spanish Stock Exchanges, while S&P500 is a value weighted index representing approximately 75 percent of the total US market capitalization.

cover all the companies listed in the market of that country. The sample period is January 1st, 1993 to April 30th, 2005[7].

The descriptive statistics in Table 1 suggest the presence of systematic intra-week patterns. For example, although overall average daily returns are positive for all markets, negative average returns are observed on Thursdays in the UK, Germany, France and Spain. Although European markets generally have higher than average returns on Mondays, the US and Germany have their highest averages on Tuesday, with the magnitude of Tuesday's return in relation to the overall average being particularly large for Germany. Tuesday also displays relatively high volatility for all markets. Alongside the low average return on Thursdays, volatility also tends to be relatively low on this day. Finally, the day-specific first-order autocorrelations suggest an end-of-week versus mid-week pattern, with positive correlations on Monday with those on the preceding Friday and on Friday with the preceding day, while the corresponding first-order correlations are often negative for the remaining days of the week.

The unconditional cross-market returns correlations in Table 2 show European markets to generally have their highest correlations with the US towards the end of the week (Thursday and Friday), and lowest correlations in the middle of the week (Tuesday and Wednesday). Indeed, the US/UK correlation on Wednesday, at .217, is less than half the corresponding correlation of .513 for Friday. However, systematic correlation patterns are less evident across European market pairs.

Although these descriptive statistics indicate the presence of day-of-the-week effects in the dynamics of stock market returns, both on an individual basis and in terms of the relationships across markets, they do not indicate the source(s) and significance of differences across days. We next turn to these issues, focusing especially on conditional correlations.

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[7] Since the data comes from different countries, it is unavoidable to have different holidays across markets. We replace a missing value by the closing price on the day before the holiday. Hence the sample for each country contains all days of the week except weekends.

5. Empirical Results

This section reports the principal results, with those for the mean and volatility discussed in the first subsection, followed by the PDCC results in subsection 5.2.

5.1 Mean and Volatility Equations

Table 3 presents estimated values of the parameters of (14) - (16), while Table 4 gives results relating to the hypotheses H_1 to H_6 outlined in section 3.2. Before considering detailed results, it should be noted that the diagnostic statistics in Table 3 indicate that these models adequately describe the variation in the conditional mean and variance of stock returns.

As seen from Table 4, there is strong evidence (at 1 % significance for either H_1, H_2, or both) of periodic effects in the mean equations for Italy, Spain and France, and the corresponding estimates in Table 3 are characterized by positive AR coefficients on Mondays and Fridays that are statistically significant at 5%, and smaller coefficients for other days that are typically insignificant and sometimes negative. The UK also displays some evidence of a PAR mean equation. Although a nonperiodic mean specification appears adequate for the remaining markets, it is nevertheless notable that estimated AR coefficients are positive and significant at 10% (or less) on Monday for all stock markets, which is compatible with results of Franses and Paap (2000), Herwartz (2000) and Bubak and Zikes (2006). Other results relating to the periodic nature of the mean equations also broadly agree with the previous literature, including Dubois and Louvet (1996), Kohers, Kohers, Kohers and Pandey (2004), Peiro (1994) and Steeley (2001).

Overall, Table 4 presents stronger evidence of the need for periodic modeling of the volatility than the mean equation, with all countries except Italy rejecting the overall hypothesis of nonperiodic volatility (H_5) at 10% or less. However, at a conventional 5% level, neither the mean nor volatility for the US is found to be periodic. Although this weak evidence of periodicity for US returns volatility is surprising in relation to the results of Franses and Paap (2000) and Bollerslev and Ghysels (1996), it should be noted that these studies use a GARCH form and hence do not account for the asymmetry evident in the estimated γ_s for the US in Table 3.

Returning to Table 4, the results relating to H_4 show that, irrespective of the significance of the overall test, all countries give evidence (at the 10% level) that volatility persistence is periodic. In other words, the volatility effects of shocks occurring on some days of the week are transferred more strongly than those occurring on other days. Although these results indicate that the nonperiodic persistency term used in previous studies is inappropriate, nevertheless, the finding that periodic volatility effects are not adequately captured by intercept shifts is in line with previous findings (Bollerslev and Ghysels 1996, Franses and Paap, 2000, Fantazzini and Rossi, 2005, Bubak and Zikes, 2006).

Interestingly, for the major international stock markets of the US, UK, Germany and France, the estimated volatility persistence parameter δ_s is largest on Thursdays, while it tends to be relatively small on Wednesdays. The highly statistically significant asymmetry parameter γ_s in the US model (at 1% for all days) contrasts with its lack of significance for some European markets at the beginning of the week (Mondays and Tuesdays). Such day-specific volatility responses presumably reflect the different nature of information released on specific days of the week, an issue to which we return below.

Although a number of individual estimated δ_s are greater than unity in Table 4, the periodic integration hypothesis H_6 is rejected for all stock markets, implying the existence of a constant, but day-specific, unconditional mean volatility.

5.2 Conditional Correlations

Table 5 reports the estimates of the persistence coefficients of the PDCC model, with Table 6 showing hypothesis test results for H_7 to H_{11} of section 3.2[8]. Notice, first, that the marginal significance level for H_7 is around 5 percent, so that shortrun persistency, measured by the coefficients A_s in (4), does not have strong periodic variation. In contrast, the hypotheses relating to non-periodicity of the overall conditional correlation model and of the longrun persistency coefficients (H_9 and H_8 respectively) are rejected at less than 0.1% significance. This not only emphasizes the inadequacy of a non-periodic DCC model in capturing the dynamics of conditional correlations between these markets, but also implies that the periodic effects relate primarily to the longrun persistency coefficients, $b_{jj,s}$. Further, the strong rejection of common PDCC coefficients across markets (H_{10}) indicates that the nature of periodicity in correlations depends on the origin of the shock. However, the decisive rejection of the null hypothesis of an integrated PDCC model (H_{11}) for all market pairs implies stability for the unconditional correlations of the shocks.

Some patterns in the periodicity of the PDCC coefficients can be seen in Table 5[9]. For instance, European markets have their highest longrun persistence coefficients at the end of the week (Friday in all cases, except for Germany where the largest value is for Thursday), whereas the US has its smallest $\hat{b}_{jj,s}$ on Friday and largest on Tuesday. Nevertheless, it is difficult to make detailed interpretations based on these coefficients alone.

To facilitate interpretation of the PDCC model, Figure 1 provides indicative plots of the patterns found in the day-specific effects in the dynamic conditional correlations across markets. For instance, the US/UK plot in panel (a) shows that, throughout the sample period, the highest

[8] Detailed results are presented in Table 5 only for the PDCC model, although restricted models were also estimated in order to compute the hypothesis tests in Table 6. In addition, a nonperiodic DCC model with coefficients constant over both countries and days ($a_{jj,s} = a$, $b_{jj,s} = b$, s = 1, 2, 3, 4, 5, j = 1, …, n) was estimated; no results are shown in relation to this last model, as the restrictions are rejected at a very high significance level.

[9] Correlations were also estimated using synchronous data (pseudo closing prices, that is prices recorded at 16:00 London time). The patterns remain qualitatively unchanged from those reported for all pair of markets.

conditional correlations between these important markets occur on Thursdays and the lowest on Tuesdays, with the former correlation being, on average, around double the latter, with other days being intermediate between these extremes. The US/France plot in panel (b) shows a broadly similar pattern to that for the US with the UK, as do other plots (not shown) for European markets with the US. Indeed, with the single exception of Italy[10], the highest conditional correlations of all European markets with the US occur on Thursdays, with the lowest being at the beginning of the week (Monday or Tuesday). The consistency of this daily pattern of correlations across European markets with the US points to the important role of the latter and implies that the high Thursday correlation may be associated with the release of economic information; we return to this below.

In addition to relationships with the US, the interrelationships between stock markets in Europe is a topic of considerable interest, especially in the context of the introduction of the euro currency (see, for instance, Cappiello et al., 2003, Savva et al., 2005). The most important euro area stock markets are those for Germany and France, and we show their conditional correlations in panel (c) of Figure 1. In the earlier part of the sample period, the highest correlations tend to occur on Tuesday, with the correlations lowest on Thursday. However, in this case day-specific effects are less marked from around week 300 (late 1998) and the relative positions alter. By the end of the sample period, the highest correlations are on Friday and the smallest on Monday and Wednesday. Another notable feature of this plot is the high level of the correlation of the shocks at the end of the sample period, with these being 0.8 or higher for all days of the week.

Similar patterns apply across many stock market pairs for Europe, especially those in the euro area. In particular, these euro area markets evidence a shift in the daily patterns of their correlations in the late 1990s, with the highest correlations subsequently applying at the end of the week (Thursdays or Fridays). Historically high correlations also apply at the end of the sample

[10] The highest Italy/US conditional correlations apply on Wednesdays, with the second highest on Thursdays.

period. A further illustration of these patterns is given by the Germany/Spain conditional correlations in panel (d) of Figure 1, where a relatively low Monday correlations from the late-1990s is particularly evident.

Finally, we also illustrate the temporal patterns in the conditional correlations between markets in European countries which are not members of the euro area with euro area members. In particular, panel (e) shows the conditional correlations for the UK and Italy, while panel (f) shows Germany and Switzerland. Once again, the highest correlations occur at the end of the week in the later part of the sample period. However, in some cases, the periodic pattern remains relatively constant over time, whereas in others it changes; indeed, panels (f) and (e), respectively, illustrate the two scenarios. When the pattern across days alters, this occurs around week 300 of the sample, which is a similar timing to the change between euro area markets and illustrated in panels (c) and (d). Many pairs involving at least one Euro Area country also show an increase in correlations at this period, which may be associated with the introduction of the euro and supports previous studies examining that issue[11].

Finally, it should be noted that the percentage differences in stock markets correlations across the days of the week can be very substantial, particularly when correlations with the US are considered, as in panels (a) and (b) of Figure 1. These are largely unchanged from the unconditional returns correlations shown in Table 2 and suggest that neglecting such effects might lead investors to make inappropriate portfolio choices.

[11] For instance see Cappiello *et. al.* (2003), Bartram, Taylor and Wang (forthcoming), Kim, Moshirian and Wu (2005), Savva, Osborn and Gill (2005) among others.

6. Discussion and Conclusions

This study investigates the presence of the-day-of-the-week effect in stock returns, volatility and correlations of six European stock markets and the US over the period from January 1993 to April 2005. More specifically, our analysis extends the periodic AR-GARCH framework to examine whether the parameters of the dynamic conditional correlation model also vary over the days of the week.

Our findings indicate the presence of day-of-the-week effects in the mean equations for most stock markets, with the notable exceptions of Germany and the US. There is also evidence of periodic variation in the coefficients of the volatility equation for all markets, although the overall hypothesis of no such variation cannot be rejected in the case of Italy. Interestingly, the leverage (asymmetry) effect in some cases varies over the days of the week. However, of most interest for this study, we find strong day-of-the-week patterns in the conditional correlations between markets. For the recent past, the correlations between European markets are highest at the end of the week (Thursdays and Fridays), while correlations of these markets with the US are often highest on Thursday and lowest at the beginning of the week.

Many explanations have been proposed to explain the intraweek patterns in stock returns, volatility and, implicitly, in conditional correlations. These are based on issues such as different settlement procedures for different days (Lakonishok and Levi, 1982; Gibbons and Hess, 1981), trading volumes (Kiymaz and Berument, 2003), the timing, origin and source of information (Penman, 1987, Gau and Hau, 2004; Brusa, Pu and Schulman, 2005), the dependence on certain economic factors and macroeconomic news (Steely, 2001 and Arshanapalli, d'Ouville, Fabozzi and Switzer, 2006).

In our case, the different pattern in conditional correlations through the week might be related to macroeconomic news announcements, namely due to the systematic pattern of news announcements on important US and European macroeconomic variables. More specifically, news releases on employment, gross domestic product, producer/consumer price indices (among others) in the US are released on pre-announced dates and specific days, and these announcements cause substantial stock and bond market volatility (Jones, Lamont and Lumsdaine, 1998). For instance, employment reports are released on Fridays, producer price index on Thursdays (until 2004) and on Fridays (from 2005 onwards), consumer price index on Wednesdays, etc (Bureau of Labor Statistics, U.S. Department of Labour)[12]. Similarly, there are scheduled announcements of macroeconomic figures for the Euro Area (monetary policy decisions are announced on Thursdays since 1999) and the publication of weekly financial statements about the assets and liabilities held by the Eurosystem[13] on Tuesdays, while UK monetary policy decisions of the Bank of England are also announced on Thursdays (since 1997). Moreover there are scheduled speeches of senior officials of the government and public agencies, etc[14].

Therefore, the high Thursday correlations we uncover, and also the high volatility persistence on this day, may be at least partially associated with economic data announcements in both US and Europe. Nevertheless, the day-of-the-week patterns sometimes change, suggesting it may be dependent on specific sample periods and markets, which supports previous evidence from Balaban *et. al* (2001). This change is particularly evident in our case around week 300, which may be associated with different timings of announcements considered relevant to the Euro Area in the latter part of the sample period compared to announcements related to individual countries for the earlier subsample.

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[12] More details are available on the webpage of Bureau of Labour Statistics (http://stats.bls.gov), European Central Bank (www.ecb.int), and Bank of England (www.bankofengland.co.uk).
[13] The Eurosystem is the central banking system of the euro area. It comprises the European Central Bank and the national central banks of those EU member states that have adopted the Euro (http://www.ecb.int/home/glossary).
[14] For further details on scheduled and unscheduled announcements in US and Europe, refer to Bauwens, Omrane and Giot (2005).

Identifying the day-of-the-week effect in mean, volatility and correlation is important for several reasons. For example investors may adjust their portfolios by increasing (reducing) their assets whose volatility is expected to reduce (increase) and use the predicted values of volatility in valuation of certain assets (such as stock index options). Investors that are interested in including international markets in their portfolios need to know if these markets are integrated and how the extent of this integration varies across the days of the week. At the same time, policymakers are interested in the impact of their policy changes, and these effects may be felt internationally. However, predictability and seasonality of stock returns found in this paper need not imply market inefficiency. In particular, the marked intra-week patterns in the conditional correlations of shocks across markets do not imply any opportunity for investment gains, but rather may simply indicate common reactions across international markets to relevant news.

This paper opens up a new dimension to the study of international stock market interactions, by showing that day-of-the-week effect are prevalent in correlation patterns across markets. Although we speculate that these patterns may be at least partly associated with announcement effects for macroeconomic data, a detailed test of this possibility is an issue for further research.

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Table 1. Descriptive Statistics for Daily Returns

	Overall	Monday	Tuesday	Wednesday	Thursday	Friday
UK						
Observations	3214	642	643	643	643	643
Mean	0.016	0.047	0.024	0.020	-0.032	0.022
Std. Deviation	1.111	1.041	1.089	1.056	0.998	1.084
Autocorrelation	0.007	0.017	-0.021	-0.001	-0.007	0.015
Germany						
Observations	3214	642	643	643	643	643
Mean	0.031	0.022	0.095	0.044	-0.002	-0.005
Std. Deviation	2.197	1.446	1.615	1.448	1.421	1.476
Autocorrelation	-0.016	0.004	-0.015	-0.019	-0.003	0.013
France						
Observations	3214	642	643	643	643	643
Mean	0.023	0.042	0.024	0.049	-0.033	0.034
Std. Deviation	1.846	1.286	1.415	1.344	1.305	1.439
Autocorrelation	0.015	0.013	-0.015	-0.006	-0.006	0.029
Italy						
Observations	3214	642	643	643	643	643
Mean	0.046	0.007	0.054	0.072	0.031	0.068
Std. Deviation	1.497	1.194	1.366	1.194	1.189	1.167
Autocorrelation	0.134	0.035	0.032	0.018	0.003	0.043
Spain						
Observations	3214	642	643	643	643	643
Mean	0.042	0.104	-0.019	0.094	-0.042	0.072
Std. Deviation	1.769	1.289	1.391	1.290	1.313	1.363
Autocorrelation	0.039	0.027	-0.019	0.001	0.009	0.021
Switzerland						
Observations	3214	642	643	643	643	643
Mean	0.032	0.056	0.044	0.015	0.020	0.024
Std. Deviation	1.381	1.110	1.289	1.177	1.063	1.226
Autocorrelation	0.042	0.018	-0.016	-0.009	0.010	0.034
USA						
Observations	3214	642	643	643	643	643
Mean	0.030	0.009	0.059	0.040	0.033	0.014
Std. Deviation	1.047	1.038	1.080	1.088	0.998	1.036
Autocorrelation	-0.014	0.009	0.010	-0.018	-0.026	0.008

Notes:
Autocorrelation values are computed in relation to the returns of the previous day.

Table 2. Unconditional Correlations for Daily Returns

	UK	Germany	France	Italy	Spain	Switz	US
Overall							
UK	1						
Germany	0.691	1					
France	0.782	0.765	1				
Italy	0.505	0.560	0.551	1			
Spain	0.686	0.691	0.775	0.538	1		
Switz	0.715	0.710	0.735	0.519	0.679	1	
USA	0.410	0.466	0.429	0.242	0.386	0.378	1
Monday							
UK	1						
Germany	0.747	1					
France	0.779	0.821	1				
Italy	0.554	0.594	0.579	1			
Spain	0.696	0.750	0.784	0.591	1		
Switz	0.756	0.788	0.781	0.579	0.726	1	
USA	0.435	0.510	0.463	0.305	0.434	0.425	1
Tuesday							
UK	1						
Germany	0.713	1					
France	0.800	0.784	1				
Italy	0.491	0.560	0.531	1			
Spain	0.674	0.667	0.772	0.482	1		
Switz	0.704	0.733	0.762	0.503	0.677	1	
USA	0.382	0.353	0.399	0.175	0.320	0.275	1
Wednesday							
UK	1						
Germany	0.688	1					
France	0.765	0.760	1				
Italy	0.449	0.533	0.532	1			
Spain	0.687	0.686	0.776	0.514	1		
Switz	0.675	0.692	0.709	0.473	0.674	1	
USA	0.257	0.402	0.296	0.134	0.280	0.280	1
Thursday							
UK	1						
Germany	0.649	1					
France	0.816	0.747	1				
Italy	0.531	0.576	0.588	1			
Spain	0.716	0.699	0.805	0.572	1		
Switz	0.737	0.671	0.726	0.542	0.687	1	
USA	0.453	0.551	0.484	0.336	0.441	0.462	1
Friday							
UK	1						
Germany	0.651	1					
France	0.746	0.705	1				
Italy	0.491	0.528	0.523	1			
Spain	0.655	0.645	0.731	0.525	1		
Switz	0.693	0.650	0.684	0.483	0.626	1	
USA	0.513	0.511	0.498	0.254	0.454	0.438	1

Table 3. Estimated PAR-PEGARCH Model for Each Market

Day	Parameter	UK	Germany	France	Italy	Spain	Switz.	USA
Monday	α_1	-0.001	0.059	0.016	0.016	-0.008	0.052	0.072**
	φ_{11}	0.134***	0.076*	0.087**	0.324***	0.199***	0.109**	0.056*
	ω_1	-0.053	0.026	0.043	-0.044	0.076	-0.086	-0.155**
	γ_1	-0.026	-0.029	-0.059***	-0.036	-0.017	-0.066**	-0.101***
	θ_1	0.101***	0.118***	0.140***	0.210***	0.167***	0.140***	0.148***
	δ_1	0.763***	1.010***	0.872***	1.098***	0.923***	0.812***	0.986***
Tuesday	α_2	0.027	0.049	0.046	0.029**	0.073*	0.023	0.010
	φ_{12}	-0.046	-0.044	-0.063*	0.081**	-0.045	-0.052	-0.041
	ω_2	0.041	-0.024	0.090	-0.007	0.036	0.165	0.078
	γ_2	-0.095***	-0.034	-0.035*	-0.038	-0.049*	-0.026	-0.079***
	θ_2	0.114***	0.159***	0.106***	0.143***	0.153***	0.184***	0.083***
	δ_2	1.256***	1.066***	1.066***	0.888***	1.001***	1.176***	0.911***
Wednesday	α_3	0.008	0.034	-0.040	0.010	-0.026	0.030	0.047*
	φ_{13}	0.028	-0.051	0.001	0.143***	0.070	0.015	0.001
	ω_3	0.042	0.170**	-0.020	-0.053	0.036	-0.167	0.027
	γ_3	-0.051***	-0.055***	-0.059***	-0.038	-0.088***	-0.097***	-0.098***
	θ_3	0.124***	0.226***	0.127***	0.218***	0.180***	0.149***	0.130***
	δ_3	0.791***	0.790***	0.775***	1.081***	0.845***	0.930***	0.953***
Thursday	α_4	0.021	-0.015	0.018	0.052	0.116***	0.040	-0.021
	φ_{14}	-0.032	-0.027	-0.055	0.084**	0.033	0.008	0.048
	ω_4	-0.090	0.070	-0.073	0.299***	0.127	0.318***	0.040
	γ_4	-0.101***	-0.058**	-0.048*	-0.041	-0.049**	-0.077**	-0.092***
	θ_4	0.141***	0.132***	0.055	0.185***	0.032	0.133***	0.070***
	δ_4	1.329***	1.118***	1.386***	0.923***	1.030***	0.925***	1.151***
Friday	α_5	0.033	0.038	0.050	0.026	0.116***	0.059*	0.015
	φ_{15}	0.022	0.014	0.098**	0.244***	0.091**	0.071*	0.037
	ω_5	0.050	-0.214*	-0.018	-0.164	-0.274	-0.222**	0.007
	γ_5	-0.064***	-0.100***	-0.068***	-0.040	-0.036	-0.147***	-0.084***
	θ_5	-0.008	0.079**	0.026	0.138**	0.075	0.130***	0.108***
	δ_5	0.933***	0.974***	0.951***	0.951***	1.146***	1.069***	0.941***
Log Likelihood		-4172.25	-5170.06	-5128.51	-4731.76	-5023.85	-4494.64	-4186.32
Q(10)		17.124* (0.072)	9.962 (0.444)	10.671 (0.384)	14.917 (0.135)	10.731 (0.379)	12.361 (0.262)	11.757 (0.302)
$Q^2(10)$		8.765 (0.555)	10.497 (0.398)	11.471 (0.322)	12.038 (0.282)	11.536 (0.317)	5.820 (0.835)	4.786 (0.905)
ARCH-LM		8.445 (0.585)	10.059 (0.435)	12.038 (0.283)	13.187 (0.213)	11.382 (0.329)	5.898 (0.824)	4.590 (0.917)

Notes:
The estimated model is given by equations (14) to (16).
*** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.
$Q(10)$ and $Q^2(10)$ are the Ljung-Box Statistics for the standardised and squared standardised residuals respectively, ARCH-LM denotes the Lagrange multiplier test for the presence of ARCH effects in the standardised residuals; p-values are in parentheses.

Table 4. Hypothesis Tests for PAR-PEGARCH Models

	Hypothesis	Degrees of freedom	UK	Germany	France	Italy	Spain	Switz.	USA
Mean Equation:									
H_1	Nonperiodic AR	4	12.865** (0.012)	6.017 (0.198)	16.146*** (0.003)	21.528*** (0.000)	20.327*** (0.000)	8.210* (0.084)	3.139 (0.535)
H_2	Nonperiodic AR; nonperiodic intercept	8	13.181 (0.106)	7.586 (0.475)	19.149** (0.014)	26.014*** (0.001)	29.939*** (0.000)	10.919 (0.206)	8.821 (0.358)
Volatility Equation									
H_3	Nonperiodic intercept	4	1.237 (0.872)	8.064* (0.089)	1.980 (0.739)	13.248** (0.010)	3.165 (0.531)	16.250*** (0.003)	6.242 (0.182)
H_4	Nonperiodic persistence	4	11.318** (0.023)	28.874*** (0.000)	9.324* (0.053)	7.879* (0.096)	43.080*** (0.000)	10.341** (0.035)	8.840* (0.065)
H_5	Nonperiodic EGARCH	16	28.055** (0.031)	32.916*** (0.000)	25.961* (0.055)	19.918 (0.224)	28.742*** (0.000)	26.468** (0.048)	25.006* (0.070)
H_6	Integrated PEGARCH	1	17.025*** (0.000)	11.876*** (0.001)	7.236*** (0.007)	8.704*** (0.003)	10.303*** (0.001)	18.655*** (0.000)	54.391*** (0.000)

Notes:
H_1 and H_2 examine periodicity in (14), while H_3 to H_5 relate to (16). All statistics are computed as Wald tests and are compared to an asymptotic χ^2 distribution, with p-values in parentheses. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Table 5. Estimated Coefficients for Dynamic Conditional Correlation Model

	UK	Germany	France	Italy	Spain	Switz.	USA
Shortrun persistence ($a_{jj,s}$)							
Monday	0.153***	0.066***	0.117***	0.102***	0.104***	0.155***	0.048***
Tuesday	0.167***	0.102***	0.068***	0.048***	0.094***	0.104***	0.065***
Wednesday	0.140***	0.117***	0.148***	0.102***	0.148***	0.105***	0.056***
Thursday	0.107***	0.101***	0.106***	0.089***	0.125***	0.078***	0.058***
Friday	0.093***	0.076***	0.069***	0.090***	0.122***	0.080***	0.036**
Longrun persistence ($b_{jj,s}$)							
Monday	1.023***	0.825***	1.075***	1.206***	0.785***	1.205***	1.025***
Tuesday	1.027***	0.950***	0.803***	0.870***	1.031***	0.876***	1.205***
Wednesday	0.867***	1.026***	1.067***	0.883***	1.165***	0.888***	0.993***
Thursday	0.902***	1.231***	0.805***	0.858***	0.818***	0.821***	0.985***
Friday	1.135***	0.988***	1.305***	1.218***	1.239***	1.225***	0.841***

Table 6. Hypothesis Tests for Periodic DCC Model

Panel A: Periodic DCC Coefficients

Hypothesis		Degrees of freedom	Statistic
H_7	Nonperiodic a_{jj}	28	41.56** (0.048)
H_8	Nonperiodic b_{jj}	28	116.78*** (0.000)
H_9	Nonperiodic DCC	56	169.56*** (0.000)
H_{10}	Simple PDCC	60	218.26*** (0.000)

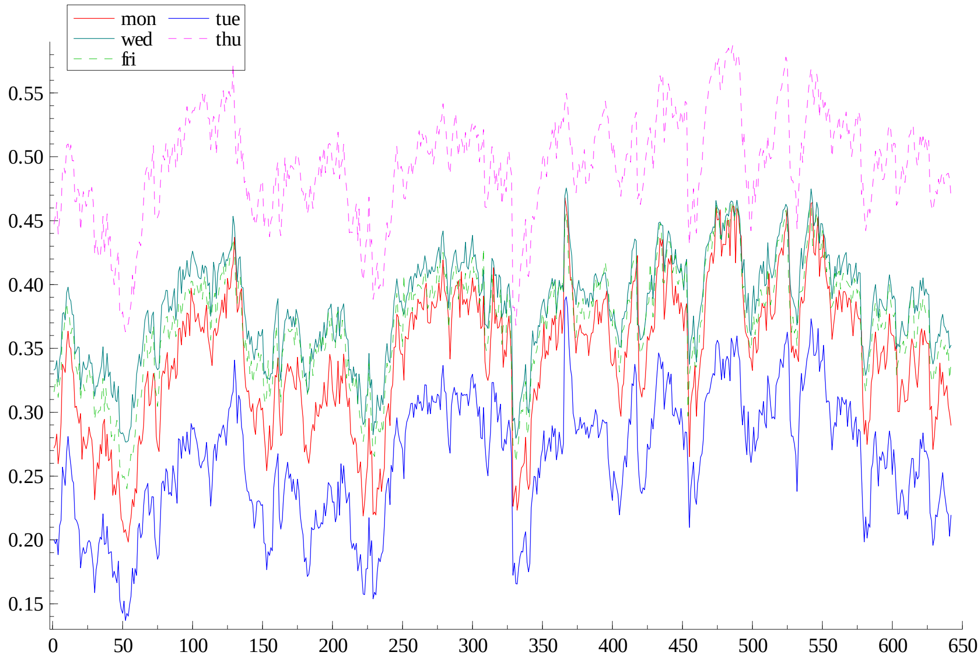
Panel B: Periodic Integration (H_{11})

	UK	Germany	France	Italy	Spain	Switz
Germany	34.120*** (0.000)					
France	45.175*** (0.0000	12.715 (0.000)***				
Italy	59.547*** (0.000)	12.688*** (0.000)	23.116*** (0.000)			
Spain	47.596*** (0.000)	17.907*** (0.000)	20.336*** (0.000)	29.805*** (0.000)		
Switz	62.960*** (0.000)	32.639*** (0.000)	48.226*** (0.000)	54.838*** (0.000)	53.859*** (0.000)	
US	52.415*** (0.000)	13.464*** (0.000)	16.974*** (0.000)	15.112*** (0.000)	28.873*** (0.000)	41.839*** (0.000)

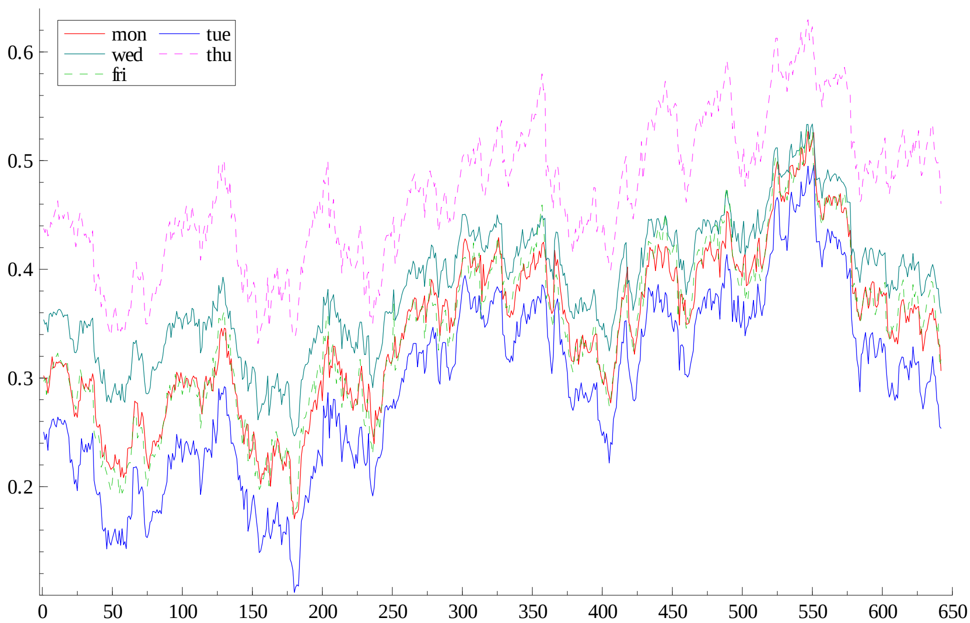
Notes:
H_6 *to* H_{10} examine periodicity in (4) using likelihood ratio test statistics. H_{11} tests the null hypothesis of an integrated periodic DCC model for the country pair using a Wald test with one degree of freedom. All statistics are tested against an asymptotic χ^2 distribution, with p-values in parentheses.
*** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Figure 1. Daily Correlation Plots

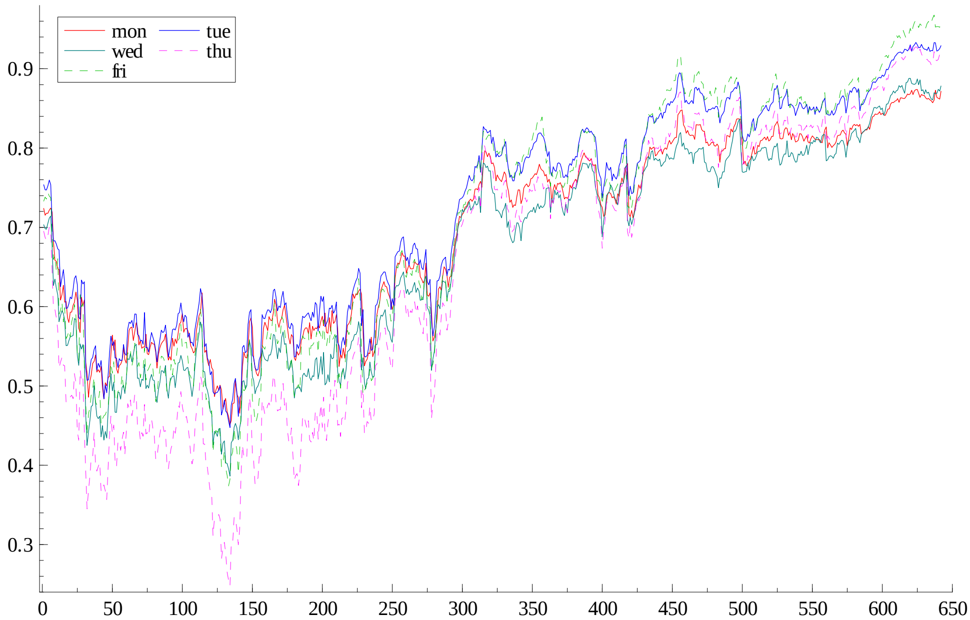
(a) US-UK



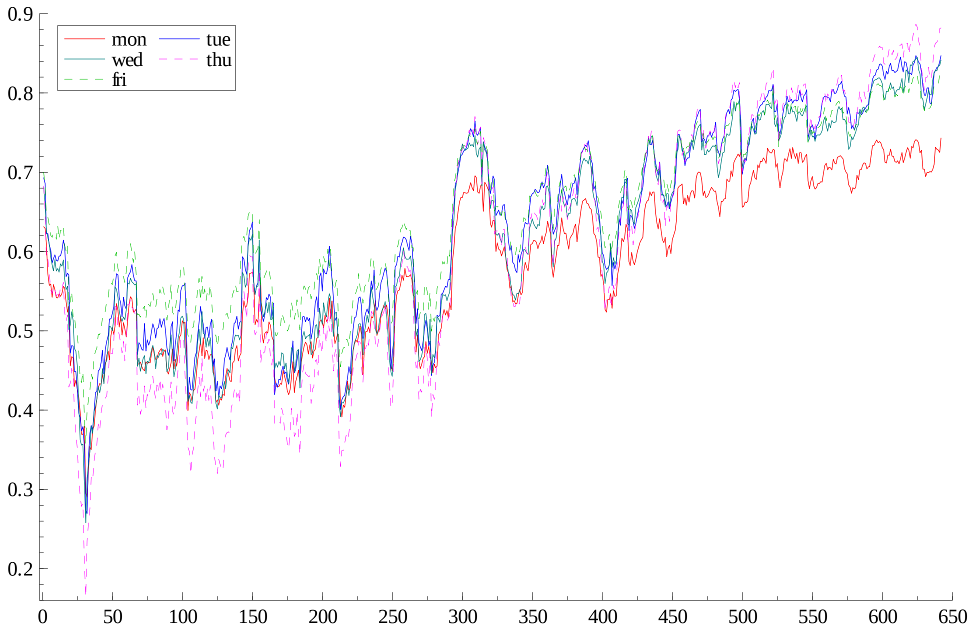
(b) US-France



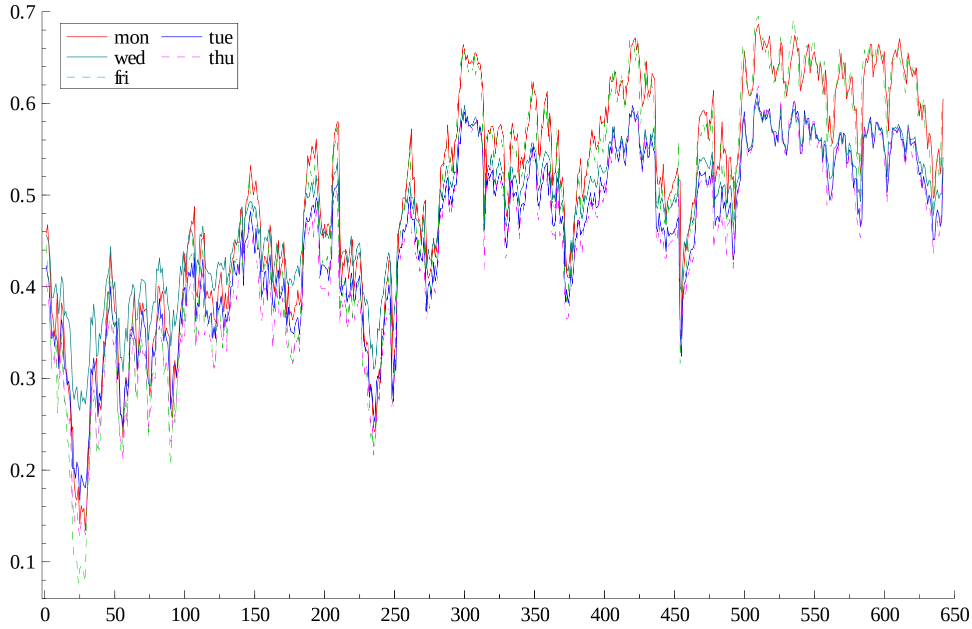
(c) Germany-France



(d) Germany-Spain



(e) UK-Italy



(f) Germany-Switzerland