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Journal of International Money and Finance
24 (2005) 413–439

Journal of International Money and Finance

www.elsevier.com/locate/econbase

Volatility linkages across three major equity markets: A financial arbitrage approach

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Abstract

This paper investigates the high frequency behavior of US, British and German stock market exuberance using an index provided by standard portfolio arbitrage relationships. Symmetric and asymmetric multivariate GARCH models are implemented to quantify international volatility linkages between January 1992 and April 2000. A shift in volatility transmission is detected from May 1997 onwards. Empirical analysis suggests that equity markets volatility modeling with exuberance indexes is more accurate than modeling with stock returns. Exuberance volatility comovements across countries are compared with the corresponding return comovements. An interpretation of their discrepancy is provided in terms of bond and stock returns international covariation.

JEL classification: F30; F40; G15

Keywords: Multivariate GARCH; Volatility transmission; Stock market exuberance

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0261-5606/$ - see front matter
doi:10.1016/j.jimonfin.2005.01.005

1. Introduction

The recent financial crises have brought about a renewed interest in theoretical and empirical investigations into international links between asset market volatilities. In most cases, however, the origins of turbulence are to be found in the emerging markets, involving financial assets often traded in a context of exchange rate and banking instability. These characteristics are incorporated in the burgeoning literature on asset market volatility "contagion" (see Masson, 1999; Kodres and Pritsker, 2002 among others).

The latter is ill-suited for investigation into the nature of the substantial stock return volatility shifts across large and sophisticated markets of industrialized countries such as the US, Britain and Germany presented in this paper. We introduce a simple model of financial arbitrage which quantifies an index of daily national stock market exuberance, and go on to investigate its behavior over time in an international context, thus encompassing two major aspects of stock market pricing analysis: international interlinkages and over-underreaction to news.

Various interpretations of excess volatility have been given, rational bubbles initially seeming to provide an appropriate explanation. Indeed, a rational bubble is compatible with the forward solution of an expected stock return model whenever the transversality condition is violated (West, 1987, among many others). More recent developments favor an interpretation of excess stock volatility in terms of fads as theoretical and empirical results reduce the plausibility of rational bubble inception. Shiller (1984) and De Bondt and Thaler (1985) point out that economic agents follow irrational trading rules and overreact to news. De Bondt and Thaler show that US stock prices tend to overreact and that extreme movements are followed by subsequent shifts in the opposite direction. Their approach has recently been extended to a multi-market context by Richards (1997) and Schnusenberg and Madura (2000), who assess (national) portfolio volatility relative to a worldwide index.

A major difficulty with over-underreaction analysis lies in the selection of a benchmark with appropriate theoretical and empirical characteristics. It can be provided either by the asset's own past history or by the (past) behavior of other assets, linked to the former by portfolio theory or arbitrage opportunities. The latter approach is followed here. The paper investigates the behavior of stock market exuberance, tentatively quantified as excess stock market return over expected long-term bond return.[1] Any positive (negative) difference in returns can be interpreted as an over-underreaction of the stock market. Fads and bubbles do not usually affect bond markets, and bond prices are generally believed to reflect economic fundamentals as the use of daily data prevents us from introducing them directly into analysis.[2]

[1] The definition of the exuberance measure used in the analysis is given below. It is related to the "holding period spread" between the rate of return of stocks and bonds used by stock market analysts to derive financial forecasts (Gray, 1993) and to the excess stock return hypothesis investigated by Fama (1981) and Zhou (1996), among others.

[2] Bubbles cannot exist if there is an upper limit on the price of an asset. Finite maturity bonds have a fixed value on the day of expiry and do not admit bubbles (Campbell et al., 1997, page 259).

In the single country context stock, bonds and money markets are interlinked in the short run as economic agents readjust their portfolios and react to the spread of news. The relevance of the correlation between stock and bond returns is somewhat controversial. Shiller and Beltratti (1992), using the VAR methodology and the present value relationships of Campbell and Shiller (1988), find that the correlation between annual excess US (and British) stock and bond returns exceeds the theoretical warranted values, and identify a possible overreaction of the stock market to the long-term bond market. Zhou (1996) finds that the power of interest rates in explaining the variation of stock market returns rises with the maturity horizon of the assets involved. Campbell and Ammer (1993) find correlation between US monthly stock and bond returns fairly weak. Applying a VAR approach, they show that the variance of excess stock returns is explained by changes in expectations of future excess stock returns, whereas the variance of excess returns on long-term nominal bonds is accounted for primarily by news about future inflation rates (in turn related to the business cycle). More recently, Bodart and Reding (1999) arrive at analogous conclusions in an international context involving European stock and bond returns volatilities. These results seem to validate our choice of exuberance index (see Section 2).

In this paper, the daily international comovement of conditional second moments of exuberance indexes from the US, British and German stock markets is investigated using multivariate GARCH parameterization, introduced in view of the volatility clustering evidenced in preliminary analysis of the data.

With respect to standard VAR modeling, multivariate GARCH is more difficult to implement. It does, however, provide the required information on the evolution over time of the volatility of the exuberance indexes and its transmission across markets—information that would not be captured by the VAR estimation approach. Indeed, with analysis of the behavior over time of the conditional variances and covariances of the set of exuberance indexes, we are able to identify the timing of the shifts in volatility and of their international linkages which, in line with previous findings, tend to increase in periods of stress. This information is of paramount relevance in a time interval—from January 1992 to April 2000—affected by bouts of severe financial turbulence. Interestingly, equity market GARCH volatility modeling with exuberance indexes seems to be more accurate—according to standard econometric criteria—than modeling with stock return time series.

This study innovates with respect to the existing literature in three ways:

- it extends exuberance analysis to an international framework: studies on stock markets interlinkages use standard stock return indexes, and research on international stock market overreaction (exuberance) transmission is somewhat sparse, as pointed out by Schnusenberg and Madura (2000);
- it compares exuberance volatility comovements across countries with the corresponding stock return comovements and provides an interpretation of their discrepancy in terms of bond and stock returns international covariation;
- it investigates explicitly whether changes in volatility do in fact Granger cause changes in exuberance comovements across markets, a highly controversial issue in the recent literature of great relevance for portfolio balancing procedures.

The paper is organized as follows. The second section introduces the theoretical model designed to extract the exuberance index and the multivariate GARCH methodology implemented to obtain estimates of conditional second moments and cross correlations between them. In the third section, the empirical findings are set out using two GARCH parameterizations of the conditional variation of the exuberance indexes over the full sample. In the fourth section, the relative accuracy of exuberance and stock return volatility estimates is assessed over two subperiods, characterized by a highly different degree of turbulence. The fifth section sets out the main conclusions.

2. Market exuberance: conditional first and second moment modeling

2.1. The theoretical model

No distinction is drawn here between nominal and real (daily) interest rates as prices are assumed to be constant in the very short run. Three non-money assets—equities, short-term government assets (Treasury bills) and long-term government bonds—enter economic agents' portfolios and are perfect substitutes but for the presence of time varying risk premia. Arbitrage between assets brings about expected one-period return equality.

Long-term bonds have $i_{\mathrm{L}t}$ yield, $P_{\mathrm{L}t}$ price and an ex ante rate of return that reads as

$$R_{\mathrm{L}t} = i_{\mathrm{L}t} + E_t\left[\frac{\Delta P_{\mathrm{L}t+1}}{P_{\mathrm{L}t}}\right] \tag{1}$$

where $E_t[\cdot]$ is the expectations operator.

Government assets arbitrage implies that

$$R_{\mathrm{L}t} = i_{\mathrm{L}t} + E_t\left[\frac{\Delta P_{\mathrm{L}t+1}}{P_{\mathrm{L}t}}\right] = i_{\mathrm{B}t} \tag{2}$$

where $i_{\mathrm{B}t}$ is the short-term (Treasury bill) rate of interest.

If s_t is the stock index price at time t, the expected one-period return on holding stocks can be defined as

$$R_{\mathrm{s}t} = E_t\left[\frac{\Delta s_{t+1}}{s_t}\right] + \frac{d_t}{s_t} \tag{3}$$

where d_t denotes dividends paid during period t.

Arbitrage between equities and short-term government assets implies that[3]

$$R_{\mathrm{s}t} = i_{\mathrm{B}t}. \tag{4}$$

Combining Eqs. (2) and (4), and using Eqs. (1) and (3), we have

$$i_{\mathrm{L}t} + E_t\left[\frac{\Delta P_{\mathrm{L}t+1}}{P_{\mathrm{L}t}}\right] = E_t\left[\frac{\Delta s_{t+1}}{s_t}\right] + \frac{d_t}{s_t}. \tag{5}$$

[3] We are disregarding here an equity premium that is documented in a large body of theoretical and empirical literature, summarised in Kocherlakota (1996).

Readjusting terms, we obtain

$$E_t\left[\frac{\Delta s_{t+1}}{s_t} - i_{\mathrm{L}t}\right] = E_t\left[\frac{\Delta P_{\mathrm{L}t+1}}{P_{\mathrm{L}t}}\right] - \frac{d_t}{s_t}. \tag{6}$$

Eq. (6) relates excess stock returns over long-term bond yields to the difference between the expected long-term bond price change and the dividend price ratio. On a daily basis d_t/s_t is very small and does not change to a perceptible extent. It can, therefore, be dropped from the specification of Eq. (6), which becomes

$$E_t\left[\frac{\Delta s_{t+1}}{s_t} - i_{\mathrm{L}t}\right] = E_t\left[\frac{\Delta P_{\mathrm{L}t+1}}{P_{\mathrm{L}t}}\right]. \tag{6$'$}$$

As an alternative, the dividend price ratio can be subsumed in the constant term of the estimates of Eq. (7) below.

As $E_t[\Delta P_{\mathrm{L}t+1}/P_{\mathrm{L}t}]$ is not observable, it has been replaced by the corresponding futures price rate of change $\Delta F_{\mathrm{L}t+1}/F_{\mathrm{L}t}$, where $F_{\mathrm{L}t}$ is the long-term bond futures price.[4]

Daily stock market exuberance is proxied by the residuals of the following regression:

$$\left[\frac{\Delta s_{t+1}}{s_t} - i_{\mathrm{L}t}\right] = \alpha + \beta\frac{\Delta F_{\mathrm{L}t+1}}{F_{\mathrm{L}t}} + u_{t+1} \tag{7}$$

where, as usual, we have replaced the expected stock price change by its ex post realized value, any discrepancy between them being reflected in the regression residual. With rational expectations and a very small dividend ratio, we would expect that $\hat{\alpha}=0$ and $\hat{\beta}=1$. The $\hat{u}_{t+1}$ time series provides the estimate of a national stock market exuberance index to be used in the empirical section below.[5] We are thus labeling an equity risk premium that subsumes both variations in stock returns and variations in expected bond prices.[6]

[4] It is well known that, for a given conversion factor, long-term bond cash and futures prices comove because of arbitrage profit opportunities, which determine the basis. An alternative estimation procedure set out by Wickens (1982) would be to replace expected bond price changes with their ex post realized values and use instrumental variables. We have discarded it, however, as the choice of instruments for assets priced in efficient markets is somewhat arbitrary; bond price rates of change (returns) show little serial correlation, which renders the traditional use of own lagged values as instruments inappropriate. Moreover, futures prices seem to react more efficiently than the corresponding bond cash prices to the arrival of news.

[5] A possible specification of the index would read as $u_{t+1} = (\Delta s_{t+1}/s_t) - i_{\mathrm{L}t} - (\Delta F_{\mathrm{L}t+1}/F_{\mathrm{L}t})$. It is too stringent, however, as it postulates that there be no dividend ratio term and disregards the possible bias introduced in the estimation using futures prices in order to quantify expected future bond prices. For a clear presentation, we define as excess stock return (ER) the expression on the left hand side of Eq. (7) and as exuberance (EX) the residual of the same equation.

[6] Eq. (7) might be interpreted in terms of APT theory. Accordingly, the excess stock return would depend upon a systemic risk, accounted for by changes in the "factor" long-term bond future prices, a specific risk, represented by the constant term, and a time varying risk premium (the residual) which is our exuberance index.

2.2. Econometric methodology

A standard finding in much of the empirical finance literature is that stock returns are serially uncorrelated—in line with the efficient market hypothesis—whereas absolute returns and squared returns are highly serially correlated because of volatility clustering. In this paper, analysis focuses on the relationship between the second conditional moments of the exuberance indexes, and a multivariate GARCH modeling procedure is called for.

The model for a multivariate GARCH is

$$\tilde{u}_{t+1}\big|\Psi_t \sim D(0, H_{t+1})$$

where $\tilde{u}_{t+1}$ is an $n \times 1$ vector of exuberance indexes, H_{t+1} is an $n \times n$ variance covariance matrix, D denotes a statistical distribution and Ψ_t is the time t information set. H_{t+1} is measurable with respect to Ψ_t and is assumed to depend on lagged values of squared and cross products of $\tilde{u}_{t+1}$ as well as on own lagged values.

Two approaches have been used to parameterize H_{t+1}, the BEKK representation of Engle and Kroner (1995) and the constant conditional correlation representation of Bollerslev (1990).

The BEKK GARCH(1,1) model has the following conditional covariance matrix

$$H_{t+1} = CC' + A_1(\tilde{u}_t\tilde{u}_t')A_1' + B_1 H_t B_1' \tag{8}$$

where C, A_1 and B_1 are $n \times n$ matrices. The advantage of this parameterization is that the presence of paired transposed matrices guarantees the symmetry and non-negativeness of H_{t+1} with no additional a priori restrictions.

The parameterization set out by Bollerslev (1990) postulates the following matrix structure

$$H_{t+1} = \begin{bmatrix} \sqrt{h_{11,t+1}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{nn,t+1}} \end{bmatrix} \Lambda \begin{bmatrix} \sqrt{h_{11,t+1}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{nn,t+1}} \end{bmatrix} \tag{9}$$

where Λ is the $n \times n$ time invariant correlation matrix and $h_{jj,t+1}$, $j = 1,\ldots,n$ is a conditional variance modeled by an univariate GARCH process. The conditional covariance $h_{jk,t+1}$ between u_{jt+1} and u_{kt+1}, the row j column k element of H_{t+1}, is given by $\rho_{jk}\sqrt{h_{jj,t+1}}\sqrt{h_{kk,t+1}}$, the product of the constant conditional correlation coefficient ρ_{jk} from matrix Λ times the conditional standard deviations of u_{jt+1} and u_{kt+1}. As is well known, positive and negative changes in financial returns have differing effects on volatility, "bad news" exerting a greater impact and justifying the use of the TGARCH approach of Glosten et al. (1993). The univariate asymmetric conditional variances of the exuberance indexes of interest are modeled as follows:

$$h_{jj,t+1} = a_0 + a_1 u_{jt}^2 + a_2 h_{jj,t} + \gamma S_t u_{jt}^2 \tag{10}$$

where $S_t = \begin{cases} 1 & \text{if } u_{jt} < 0 \\ 0 & \text{if } u_{jt} \geq 0 \end{cases}$.

3. International linkages between exuberance indexes: the empirical findings

In this section the multivariate GARCH technique is used to analyze the behavior over time of covariances between stock market exuberance indexes. First the data are described and the choice of model motivated empirically. The estimates are then performed over the whole sample.

3.1. Data, preliminary statistics and univariate analysis

Study of the international volatility linkages between stock market exuberance indexes focuses on the financial centers of three major industrialized countries: the US, Great Britain and Germany. The daily data set runs from January 3, 1992 to April 20, 2000.

The DJIA, FTSE100 and DAX100 are used, respectively, as US, British and German stock market indexes. The nominal long-term interest rates are the redemption yields of long-term (10-year) government bonds and are provided by Datastream under the acronyms GBUS10Y, GBUK10Y and GBBD10Y. The settlement prices of the CBOT-US Treasury bond, LIFFE Long Gilt and Eurex-Euro Bund futures contracts are used to proxy the corresponding expected long-term bond prices. Futures time series are continuous and correspond to the nearest (to expiry) contract month. They switch to the next contract following the standard Datastream rollover procedure and are labeled by the acronyms CUSCS00, LIGECS00 and GGEECS00.[7]

Daily percentage stock market returns s_t are calculated as logarithmic difference in daily stock index prices, i.e., $s_{t+1} = 100\,(\log(S_{t+1}) - \log(S_t))$, where S_t is the index in levels. In the same way, daily expected percentage bond price changes y_t are quantified as logarithmic first differences in the corresponding futures contract prices, i.e., $y_{t+1} = 100\,(\log(F_{\mathrm{L}t+1}) - \log(F_{\mathrm{L}t}))$, where $F_{\mathrm{L}t}$ is the futures contract price. Nominal interest rates are quoted on a daily basis.

Table 1, panel a, gives some of the key features of the variables that enter the paper. The series are stationary, as shown by the ADF test statistics, and the Jarque Bera tests detect substantial deviations from normality in the distributions, due mostly to a high level of kurtosis. Ljung Box Q-statistics detect some serial correlation in the return and excess return UK time series only.

A measure of exuberance on each stock market is provided by the OLS residuals of Eq. (7). Table 2 investigates the Granger causality direction between the regressand—i.e., the difference between stock index returns and long-term interest rate—and the corresponding regressor—i.e., the long-term bond futures price rate of change. At lag 2, the causality direction runs from the regressor to the regressand for all countries, with probability of type I error no higher than 7%, a finding that

[7] For instance, the CBOT-US Treasury bond futures contract has a trading cycle with expiration in March, June, September and December. During March prices from the June contract are taken for the futures time series until the first business day of June, when the September contract takes over, even if the June contract is still trading.

Table 1
Statistical characteristics of government bond futures price rates of change, and of stock market returns and excess returns

	ERUS	ERUK	ERBD	YUS	YUK	YBD	DLDJIA	DLDAX	DLFTSE
Panel a									
1/3/1992–4/20/2000									
Mean	0.032	0.015	0.034	0.002	0.014	0.008	0.056	0.058	0.042
Median	0.006	−0.016	0.030	0.000	0.000	0.000	0.031	0.053	0.011
Std. Dev.	0.899	0.932	1.109	0.371	0.522	0.345	0.899	1.108	0.932
Skewness	−0.541	0.019	−0.473	−0.390	0.093	−0.502	−0.545	−0.480	0.012
Kurtosis	9.549	5.272	7.259	5.316	8.192	6.151	9.554	7.269	5.278
JB	3973+	465.5+	1717+	538.7+	2434+	985.8+	3980+	1726+	467.9+
LB(1)	0.76	15.76++	2.89	2.74	0.23	1.07	0.75	2.86	15.73++
LB(5)	10.42	28.09++	8.61	17.01++	1.44	3.25	10.46	8.59	28.10++
ADF(10)	−14.45*	−13.86*	−14.01*	−14.10*	−14.35*	−14.48*	−14.46*	−14.03*	−13.90*
Panel b									
1/3/1992–5/30/1997									
Mean	0.033	0.012	0.019	0.001	0.010	0.010	0.058	0.045	0.043
Median	0.010	−0.022	−0.008	0.000	0.011	0.000	0.035	0.021	0.008
Std. Dev.	0.669	0.733	0.807	0.388	0.563	0.346	0.669	0.807	0.733
Skewness	−0.279	0.253	−0.317	−0.428	−0.096	−0.574	−0.278	−0.318	0.257
Kurtosis	4.692	6.759	5.019	5.428	6.382	6.630	4.694	5.026	6.772
JB	186.7+	845.6+	263.4+	389.7+	674.6+	852.2+	186.9+	265.1+	851.9+
LB(1)	1.93	4.03	0.06	0.45	1.37	0.22	1.91	0.05	3.99
LB(5)	10.33	4.65	5.78	9.03	3.91	2.42	10.37	5.68	4.59
ADF(10)	−11.79*	−11.41*	−11.80*	−11.35*	−11.65*	−11.89*	−11.80*	−11.84*	−11.42*
Panel c									
6/2/1997–4/20/2000									
Mean	0.030	0.018	0.065	0.003	0.020	0.005	0.052	0.083	0.040
Median	−0.009	−0.007	0.121	0.000	0.000	0.009	0.015	0.140	0.014
Std. Dev.	1.218	1.220	1.520	0.337	0.437	0.342	1.218	1.520	1.220
Skewness	−0.534	−0.085	−0.482	−0.262	0.864	−0.362	−0.535	−0.482	−0.086

Kurtosis	7.335	3.504	5.187	4.557	15.16	5.219	7.336	5.187	3.504
JB	626.3+	8.870+	179.5+	84.76+	4736+	171.1+	626.6+	179.5+	8.894+
LB(1)	0.09	9.94++	1.74	5.07++	2.45	6.01	0.09	9.96++	1.75
LB(5)	5.45	24.08++	7.45	12.69++	3.99	7.86	5.46	24.06++	7.34
ADF(10)	−8.73*	−8.50*	−8.72*	−8.69*	−9.16*	−8.55*	−8.74*	−8.50*	−8.71*

The total number of observations is 2164. All variables are expressed in daily rates.

Notes: JB, Jarque Bera normality test statistic; ADF(10), unit root ADF test statistic of order 10; LB(j), Ljung Box Q-test statistic for jth order serial correlation; (+) indicates rejection of the normality hypothesis at the 5% significance level; (*) indicates rejection of the unit root hypothesis at the 5% significance level; (++) indicates the rejection of the hypothesis of no autocorrelation at lag j.

General warning: For all the variables the following suffixes US, UK and BD identify, respectively, the US, British and German market.

ERUS(_UK, _BD): Excess stock market return, defined as the difference between the daily stock market return and the 10-year government bond yield measured on a daily basis.

YUS(_UK, _BD): Expected capital gain or loss on long-term government bonds defined as the $(t+1)$ first difference of the logarithm of the settlement price of the futures contracts on long-term government bonds.

DLDJIA(_FTSE,_DAX): Stock market return defined as the $(t+1)$ first difference of the logarithm of the stock market price index.

Table 2
Granger causality test between the stock market excess return and the expected rate of change of long-term government bond prices

1/3/1992–4/20/2000						
	ERUS → YUS	YUS → ERUS	ERUK → YUK	YUK → ERUK	ERBD → YBD	YBD → ERBD
Lags 2	0.20 [0.81]	2.56 [0.07]**	0.49 [0.61]	3.24 [0.03]*	1.25 [0.28]	11.38 [0.00]*
Lags 5	0.97 [0.42]	1.29 [0.26]	1.44 [0.20]	3.24 [0.00]*	0.92 [0.46]	4.78 [0.00]*
Lags 10	0.72 [0.70]	0.74 [0.67]	1.27 [0.23]	1.82 [0.05]*	1.15 [0.31]	3.43 [0.00]*

Notes: (*) indicates rejection of the null hypothesis (no Granger causality) at the 5% significance level; (**) indicates rejection at the 10% significance level; probability values are in square brackets.
For all the variables the following suffixes US, UK and BD identify, respectively, the US, British and German market.
ERUS(_UK, _BD): Excess stock market return, defined as the difference between the daily stock market return and the 10-year government bond yield measured on a daily basis.
YUS(_UK, _BD): Expected capital gain or loss on long-term government bonds defined as the first difference of the logarithm of the settlement price of the futures contracts on long-term government bonds.

justifies the OLS estimation of Eq. (7). The results, set out in Table 3 justify the caveats of the theoretical section (see footnote 5): if the constant α is not significantly different from zero, in line with our assumptions, β estimates are significantly below 1. The statistical properties of the exuberance time series (i.e., the residuals of Eq. (7)) are set out in Table 4, panel a. Over the whole sample they are broadly similar to those of the corresponding return and excess return time series.

The LM ARCH tests in Table 3 are always highly significant and detect the presence of residual conditional heteroskedasticity. Indeed, exuberance conditional variance can be given a satisfactory TGARCH(1,1) parameterization, which is set out in Table 5.[8] Coefficient γ is positive and significant, in line with the hypothesis that bad news has a larger impact on the conditional variance.

We find strong evidence of a structural volatility shift on May 30, 1997: the coefficient φ of a step dummy (0–1) is always highly significant and suggests a volatility increase beyond that date. The sample is thus split at the inception of the Asian crisis (set to coincide with the speculative attack on Thailand's baht in May 1997), which justifies a partitioning from January 3, 1992 to May 30, 1997 and from June 2, 1997 to April 20, 2000.[9] Shifts in the pattern of stock market volatility during recent financial crises have, in fact, been identified in previous works, such as Baig and Goldfajn (1999) among many others.

The statistical properties of the return, excess return and exuberance time series in these subperiods, set forth in panels b and c of Tables 1 and 4, do not contradict the

[8] Comparison of the Arch tests across Tables 3 and 5 suggests that this specification accounts for most exuberance conditional heteroskedasticity: the test statistics decrease sharply in Table 5 and are no longer significant.
[9] Complete chronological descriptions of the crisis are provided by various sources, among which the *IMF World Economic Outlook* May 1998, December 1998, and May 1999 issues.

Table 3
OLS estimates of Eq. (7)

	US	UK	BD
α (s.e.)	0.031 (0.02)	0.007 (0.02)	0.030 (0.02)
β (s.e.)	0.430 (0.06)*	0.510 (0.05)*	0.530 (0.08)*
R^2	0.031	0.083	0.027
DW	1.95	1.80	1.96
Arch(12) [prob]	226.57 [0.00]	347.59 [0.00]	319.21 [0.00]

Notes: White heteroskedasticity-consistent standard errors; Arch(j), Breusch Pagan test for jth order conditional heteroskedasticity; (*), significant at the 5% level.

hypothesis of a regime shift. Ljung Box Q-statistics indicate that serial correlation of the time series is more marked in the second (turbulent) subperiod than in the first.

As for the means and standard deviations, various dissimilarities are detected across the two subperiods. Before the crisis (see panel b of the tables), daily excess stock returns range, on average, between 0.033% in the US market and 0.012% in the British market, while the average stock market exuberance is close to nil. In the second subperiod, analyzed in panel c of the tables, both excess stock returns and stock market exuberance indexes tend to rise on average, the latter reaching 0.05% in the German market.

Average standard deviations of stock returns, excess returns and exuberance indexes also differ significantly across periods, being lower (less than 1%) in the first than in the second when they lie in the 1.2–1.5% range.

The correlation indexes, which provide a rough measure of interdependence, are given in Table 6. Correlation between the US and German markets seems to be more marked than between the US and British ones. A remarkable feature is the sharp increase in correlation index between British and German stock market exuberances, from 0.34 in the first period to 0.68 in the second. Here, we postulate a shift in the correlation structure; two different views have been expressed on this question. Koutmos and Booth (1995) among others, suggest that the increase in correlation is a function of time, i.e., the outcome of an increase in stock market linkages in recent years. Longin and Solnik (1995) and, more recently Ramchand and Susmel (1998), Domanski and Kremer (2000) and Jochum (2001) maintain that increases in correlation coefficients are temporary and coincide with increases in volatility.

Following Kaplanis (1988) the stability of the correlation coefficients among both the exuberance and stock return indexes is investigated using the Jenrich χ^2 test of equality of two matrices (Jenrich, 1970, equations (4.1)–(4.6), page 908). We estimate the unconditional correlation matrices over adjacent subperiods, in the full sample and in the two subsamples postulating alternative breakpoints.[10] The results (see Table 7) corroborate the dating of the sample partitioning; the statistics strongly

[10] A modified version of the test (equation (7.2), page 911) compares the correlation matrices of exuberances and stock returns over the full sample. The null hypothesis (of matrix equality) is rejected more strongly in the first subperiod. This finding validates the hypothesis that exuberance indexes have their own specific nature.

Table 4
Statistical characteristics of exuberance indexes

	Panel a			Panel b			Panel c		
	1/3/1992–4/20/2000			1/3/1992–5/30/1997			6/2/1997–4/20/2000		
	EXUS	EXUK	EXBD	EXUS	EXUK	EXBD	EXUS	EXUK	EXBD
Mean	0.000	0.009	0.017	0.001	0.008	0.000	−0.003	0.009	0.049
Median	−0.035	−0.010	0.004	−0.035	−0.009	−0.017	−0.036	−0.014	0.113
Std. Dev.	0.884	0.892	1.094	0.622	0.632	0.763	1.234	1.241	1.533
Skewness	−0.652	−0.028	−0.554	−0.225	0.181	−0.246	−0.631	−0.076	−0.570
Kurtosis	10.85	6.050	7.929	4.500	6.350	4.571	7.681	3.846	5.433
JB	5704+	839.3+	2302+	144.2+	667.4+	159.3+	738.5+	23.21+	226.7+
LB(1)	0.93	20.26++	0.42	3.44	6.94++	4.31	0.05	10.50++	1.18
LB(5)	9.26	40.47++	5.89	10.39	8.88	13.49++	5.18	29.78++	7.09
ADF(10)	−14.01*	−14.06*	−13.79*	−11.85*	−11.75*	−11.43*	−8.67*	−8.73*	−8.70*

All variables are expressed in daily rates.
Notes: JB, Jarque Bera normality test statistic; ADF(10), unit root ADF test statistic of order 10; LB(j), Ljung Box Q-test statistic for jth order serial correlation; (+) indicates rejection of the normality hypothesis at the 5% significance level; (*) indicates rejection of the unit root hypothesis at the 5% significance level; (++) indicates the rejection of the hypothesis of no autocorrelation at lag j.
EXUS(_UK, _BD): Exuberance on the stock market, calculated as the residual of the OLS regression in Table 3.

reject the null hypothesis of no break point in May 30, 1997 when the test is carried out over full sample. At the same time, the null is overwhelmingly accepted whenever alternative breakpoints are investigated in the two subsamples. The correlation structure seems to be stable within the January 1992–May 1997 and June 1997–April 2000 subperiods.[11]

3.2. International volatility linkages

Maximum likelihood estimates of the multivariate model for the whole sample are presented in Tables 8 and 9.[12] Table 8 gives the parameters of the BEKK representation and Table 9, those of the Constant Conditional Correlation Threshold GARCH.

[11] Forbes and Rigobon (2002), Loretan and English (2000) and Ronn et al. (2001) suggest that sample correlations tend to increase relative to a constant population moment whenever the sampling variance of the relevant time series exceeds its long-run unconditional variance. Hence upward shifts in correlation, in periods of turbulence, are to be found even if the true correlation remains invariant. The relevance of these critiques is limited by the necessarily ad hoc selection of the time interval over which the long-run "true" unconditional variance is to be measured. In the constant conditional correlation GARCH analysis of Tables 9 and 10, time varying conditional covariances are assumed to be proportional to the square root of the product of the corresponding two conditional variances. The effect of shifts in volatility is thus accounted for by the joint ML conditional correlation and variance estimation (see Bollerslev, 1990, equations (6)–(7), page 500). In Table 10 stock exuberance conditional correlations rise in the second, more volatile, time period, in line with the findings of Tables 6 and 7.

[12] The US variables are lagged by one business day in order to compensate for non-synchronous trading times.

Table 5
Univariate TGARCH(1,1) estimates of exuberance index conditional variances
$h_{t+1} = a_0 + a_1 u_t^2 + a_2 h_t + \gamma S_t u_t^2 + \varphi D_{t+1}$

	US	UK	BD
a_0 (s.e.)	0.026 (0.00)*	0.006 (0.00)*	0.024 (0.01)*
a_1 (s.e.)	0.017 (0.02)*	0.009 (0.01)*	0.045 (0.02)*
a_2 (s.e.)	0.856 (0.03)*	0.947 (0.01)*	0.884 (0.02)*
γ (s.e.)	0.123 (0.03)*	0.055 (0.01)*	0.061 (0.03)*
φ (s.e.)	0.060 (0.02)*	0.018 (0.01)*	0.057 (0.02)*
Std. residuals tests			
Arch(1) [prob]	0.39 [0.53]	0.49 [0.48]	0.17 [0.67]
Arch(12) [prob]	9.30 [0.67]	15.06 [0.23]	4.84 [0.96]

Notes: Bollerslev–Wooldridge robust standard errors; Arch(j), Breusch Pagan test for jth order conditional heteroskedasticity; (*), significant at the 5% level.

The quality of fit in Table 8 is satisfactory. The exuberance indexes are obtained as residuals of properly specified first-stage regressions (Eq. (7)) and, as expected, the constant terms of the conditional mean equations are not significantly different from zero. They are not given here for lack of space. Most coefficients of the conditional variance and covariance equations (c_{ij}, α_{ij} and β_{ij} in Table 8) are highly significant and suggest that the fitted model is second-order stationary and that the unconditional second moments exist. Second-moment interdependency can be detected as the conditional variance in each market is also affected by innovations in the other markets. The Breusch Pagan tests find no marked evidence of residual conditional heteroskedasticity. A t distribution has been used to model the conditional distribution of the system as the Jarque Bera statistic rejects the hypothesis of conditional normality.[13]

In order to introduce the leverage effect—a stylised fact in asset pricing volatility dynamics detected by the univariate analysis above—a multivariate Threshold GARCH (TGARCH) with constant conditional correlations is estimated, following the approach set out in Section 2.2. The quality of fit (Table 9) is satisfactory here, too, and two out of three leverage effect coefficients γ are positive and statistically significant. The Jarque Bera and Arch test statistics are similar to those obtained with the BEKK parameterization. According to the Akaike and Schwarz Bayesian Information Criteria (which correspond, respectively, to the AIC and BIC acronyms set forth in the tables), the difference between the two models is difficult to ascertain. The significance of the leverage coefficients, however, and comparison between the respective BDS statistics and AutoCorrelation Functions of the Euclidean norm (i.e., the square root of the sum of squares of the elements of the diagonal vector) of the standardized residuals, seem to support the choice of a TGARCH trivariate

[13] Conditional non-normality implies that even if the coefficient estimates are consistent, the corresponding standard errors are biased and tend to underestimate their true theoretical values. The significance of the estimates given in Tables 8–10 is, however, very high, and cannot be attributed to this bias, for any reasonable value of the latter.

Table 6
Unconditional correlation indexes

	ERUS1	ERUK	ERBD	EXUS1	EXUK	EXBD	DLDJIA1	DLFTSE	DLDAX
1/3/1992–4/20/2000									
ERUS1	1.00								
ERUK	0.28	1.00							
ERBD	0.39	0.58	1.00						
EXUS1	0.98	0.28	0.37	1.00					
EXUK	0.29	0.96	0.57	0.30	1.00				
EXBD	0.38	0.54	0.98	0.38	0.56	1.00			
DLDJIA1	1.00	0.28	0.39	0.98	0.29	0.38	1.00		
DLFTSE	0.28	1.00	0.58	0.28	0.96	0.54	0.28	1.00	
DLDAX	0.39	0.58	1.00	0.37	0.57	0.98	0.39	0.58	1.00
1/3/1992–5/30/1997									
ERUS1	1.00								
ERUK	0.21	1.00							
ERBD	0.40	0.43	1.00						
EXUS1	0.97	0.21	0.36	1.00					
EXUK	0.22	0.92	0.38	0.22	1.00				
EXBD	0.40	0.33	0.96	0.37	0.34	1.00			
DLDJIA1	1.00	0.21	0.40	0.97	0.22	0.40	1.00		
DLFTSE	0.21	1.00	0.43	0.21	0.92	0.33	0.21	1.00	
DLDAX	0.40	0.43	1.00	0.36	0.38	0.96	0.40	0.43	1.00
6/2/1997–4/20/2000									
ERUS1	1.00								
ERUK	0.32	1.00							
ERBD	0.38	0.68	1.00						
EXUS1	0.99	0.33	0.38	1.00					
EXUK	0.32	0.98	0.67	0.33	1.00				
EXBD	0.37	0.67	0.99	0.38	0.68	1.00			
DLDJIA1	1.00	0.32	0.38	0.99	0.32	0.37	1.00		
DLFTSE	0.32	1.00	0.68	0.33	0.98	0.67	0.32	1.00	
DLDAX	0.38	0.68	1.00	0.38	0.67	0.99	0.38	0.68	1.00

Note: The variables with suffix 1 are lagged by one working day.

conditional variance specification, which is adopted in the subsequent analysis. The BDS statistics from the German and UK BEKK estimates are large in absolute value; they reject the null that the standardized residuals are independent and identically distributed (iid) whenever the embedding dimension is higher than two, a symptom of leftover non-linearity.[14] The TGARCH BDS statistics reject the null in the German case only. The AutoCorrelation Functions of the norm of the standardized residuals of both parameterizations (set out in Fig. 1) improve upon

[14] The BDS portmanteau test for time-based dependence has been discussed by Brock et al. (1987). It follows an asymptotic $N(0,1)$ distribution under the null. Brock et al. (1991, chapter 2) provide Monte Carlo evidence that this asymptotic distribution may be affected when using GARCH standardized residuals and be biased in favor of the GARCH specification. Reported in the tables, therefore, are bootstrapped probability values computed using the routine set out in Eviews 4.0, with 1000 repetitions.

Table 7
Jenrich tests for the stationarity of the correlation matrices

H_0: $corr_1 = corr_2$		Jenrich χ^2	
Periods compared		Exuberance indexes	Returns
1	2		
1/06/92	6/02/97	87.146*	58.749*
5/30/97	4/20/00	[0.0]	[0.0]
1/06/92	1/01/93	4.583	3.822
12/31/92	5/30/97	[0.205]	[0.281]
1/06/92	1/03/94	8.673*	15.128*
12/31/93	5/30/97	[0.034]	[0.002]
1/06/92	1/02/95	3.883	6.528
12/30/94	5/30/97	[0.274]	[0.088]
1/06/92	1/01/96	5.194	5.001
12/29/95	5/30/97	[0.158]	[0.172]
1/06/92	1/01/97	3.202	3.714
12/31/96	5/30/97	[0.361]	[0.294]
6/02/97	1/01/98	2.980	2.043
12/31/97	4/20/00	[0.394]	[0.563]
6/02/97	1/01/99	2.371	3.401
12/31/98	4/20/00	[0.499]	[0.334]
6/02/97	1/03/00	8.766*	6.186
12/31/99	4/20/00	[0.033]	[0.103]

Notes: χ^2, chi-square statistic with 3 degrees of freedom; probability values are in square brackets; (*), the null hypothesis is rejected at the 5% level of significance.

the AutoCorrelation Function of the norm of the observations, which identifies a significant correlation structure due to heteroskedasticity. However, the improvement associated with the TGARCH standardized residuals seems to be more substantial as no significant autocorrelation is found beyond the third order, whereas the coefficients of the BEKK residuals exceed the 5% significance boundary at higher order lags.[15]

It should be noted that with both parameterizations, exuberance indexes produce information statistics smaller than those obtained applying the same models to the corresponding return time series: the AIC for the full sample BEKK and CCC.TGARCH return conditional variance models (not reported here) are, respectively, 15405 and 15391.[16] This, by virtue of the very nature of these statistics, implies a higher explanatory power for the exuberance approach.

[15] Ding and Granger (1996) suggest that a more suitable modeling of the volatility clustering of stock returns is provided by a Power GARCH parameterization with power $d = 1$, i.e., that absolute values of the return series be more appropriate than squares as volatility proxies. Both the univariate and multivariate analyses above were repeated according to this methodology. When the leverage term is introduced, no convergence is achieved in the multivariate estimation of the second subperiod. Whenever the power parameter d is estimated, its values are in the neighborhood of 2 and the PGARCH model converges to a standard GARCH.

[16] This result holds even if we adjust for the 6 "latent" coefficients of the exuberance index regressions (7).

Table 8
Multivariate BEKK(1,1) estimates of stock exuberances (conditional t distribution)

1/3/1992–4/20/2000			
t degree of freedom 10.30 (s.e.: 1.043)	BEKK(1,1)		
	US ($j = 1$)	UK ($j = 2$)	BD ($j = 3$)
Conditional variance covariance	$H_{t+1} = CC' + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{bmatrix} v_{11} & v_{12} & v_{13} \\ v_{21} & v_{22} & v_{23} \\ v_{31} & v_{32} & v_{33} \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{21} & \alpha_{31} \\ \alpha_{12} & \alpha_{22} & \alpha_{32} \\ \alpha_{13} & \alpha_{23} & \alpha_{33} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} H_t \begin{bmatrix} \beta_{11} & \beta_{21} & \beta_{31} \\ \beta_{12} & \beta_{22} & \beta_{32} \\ \beta_{13} & \beta_{23} & \beta_{33} \end{bmatrix}$		
$c_{1,j}$ (s.e.)	0.094 (0.01)*		
$c_{2,j}$ (s.e.)	−0.041 (0.02)*	0.104 (0.02)*	
$c_{3,j}$ (s.e.)	0.011 (0.09)	−0.075 (0.58)	0.032 (1.35)
$\alpha_{1,j}$ (s.e.)	0.144 (0.02)*	−0.075 (0.01)*	−0.050 (0.02)*
$\alpha_{2,j}$ (s.e.)	0.079 (0.02)*	0.108 (0.01)*	0.025 (0.02)
$\alpha_{3,j}$ (s.e.)	0.050 (0.02)*	0.052 (0.01)*	0.246 (0.02)*
$\beta_{1,j}$ (s.e.)	0.971 (0.01)*	0.029 (0.00)*	−0.002 (0.01)
$\beta_{2,j}$ (s.e.)	−0.004 (0.01)	0.983 (0.00)*	0.017 (0.01)
$\beta_{3,j}$ (s.e.)	−0.023 (0.01)*	−0.008 (0.01)	0.944 (0.01)*
AIC		14795.53	
BIC		14954.56	
Tests on std. residuals			
JB [prob]	321.86 [0.00]	46.22 [0.00]	111.35 [0.00]
BDS(2) [prob]	−0.3386 [0.79]	1.8359 [0.08]	1.5881 [0.12]
BDS(4) [prob]	−0.3922 [0.73]	3.4732 [0.00]	2.4680 [0.03]
Arch(12) [prob]	16.66 [0.21]	35.95 [0.01]	18.17 [0.17]

Notes: $v_{jk} = u_j u_k$; (*), significant at the 5% level; JB, Jarque Bera normality test statistic; Arch(12), Breusch Pagan test for 12th order conditional heteroskedasticity; AIC, Akaike Information Criterion; BIC, Schwarz Bayesian Information Criterion; BDS(j), Brock–Dechert–Scheinkman test statistic with embedding dimension $j = 2$ and 4. The corresponding *distance* is a multiple of the standard deviation of the series.

Table 9
Multivariate TGARCH(1,1) estimates of stock exuberances (conditional t distribution)

1/3/1992–4/20/2000			
t degree of freedom 10.28 (s.e.: 1.041)	Constant Conditional Correlation-TGARCH (1,1)		
	US ($k = 1$)	UK ($k = 2$)	BD ($k = 3$)
Variance equation			
a_0 (s.e.)	0.006 (0.00)*	0.003 (0.00)*	0.013 (0.00)*
a_1 (s.e.)	0.025 (0.01)*	0.004 (0.00)*	0.048 (0.01)*
a_2 (s.e.)	0.930 (0.01)*	0.961 (0.01)*	0.911 (0.01)*
γ (s.e.)	0.040 (0.01)*	0.041 (0.01)*	0.012 (0.01)
AIC		14811.61	
BIC		14902.49	
CCC			
ρ_{1k} (s.e.)		0.2332 (0.02)*	0.3430 (0.02)*
ρ_{2k} (s.e.)			0.4557 (0.02)*
Tests on std. residuals			
JB [prob]	439.64 [0.00]	57.45 [0.00]	110.82 [0.00]
BDS(2) [prob]	−0.6443 [0.56]	−0.5188 [0.64]	2.5133 [0.02]
BDS(4) [prob]	−0.9802 [0.35]	0.7332 [0.41]	3.7981 [0.00]
Arch(12) [prob]	13.51 [0.33]	20.00 [0.07]	14.89 [0.24]

Notes: JB, Jarque Bera normality test statistic; (*), significant at the 5% level; Arch(12), Breusch Pagan test for 12th order conditional heteroskedasticity; AIC, Akaike Information Criterion; BIC, Schwarz Bayesian Information Criterion; BDS(j), Brock–Dechert–Scheinkman test statistic with embedding dimension $j = 2$ and 4. The corresponding *distance* is a multiple of the standard deviation of the series.

The constant conditional correlation coefficients are given by the sample correlation matrix and are set out in Table 9, under the heading CCC. They are highly significant and suggest that the German market is the most interdependent. Fig. 2 shows the corresponding standardized residuals and the conditional standard deviations over the whole sample. A shift in the volatility estimates in the summer of 1997 is readily identified, and supports the dating of the sample partitioning.

In the same way, the conditional covariances set out in Fig. 3 show a huge rise from 1997 onwards and seem to validate the hypothesis of a shift in the pattern of the comovements of stock exuberance conditional volatility. The full sample conditional covariances display three peaks at dates that are common to the three indexes of interest. The first (smallest) peak corresponds to the EMS collapse of September–October 1992, the second to the Hong Kong stock market crash in October 1997, and the third, from August 1998 to January 1999, encompasses the Russian and Brazilian financial crises. Comparison between the first and the second rows of Fig. 3 shows that volatility transmission across countries is mostly accounted for by stock market exuberance: return covariances are de facto exuberance covariances.

4. Pre- and post-crisis volatility transmission

Two main factors justify the decision to partition the sample in two: the empirical evidence provided in Section 3.2, and the suggestion by Bollerslev et al. (1992) that

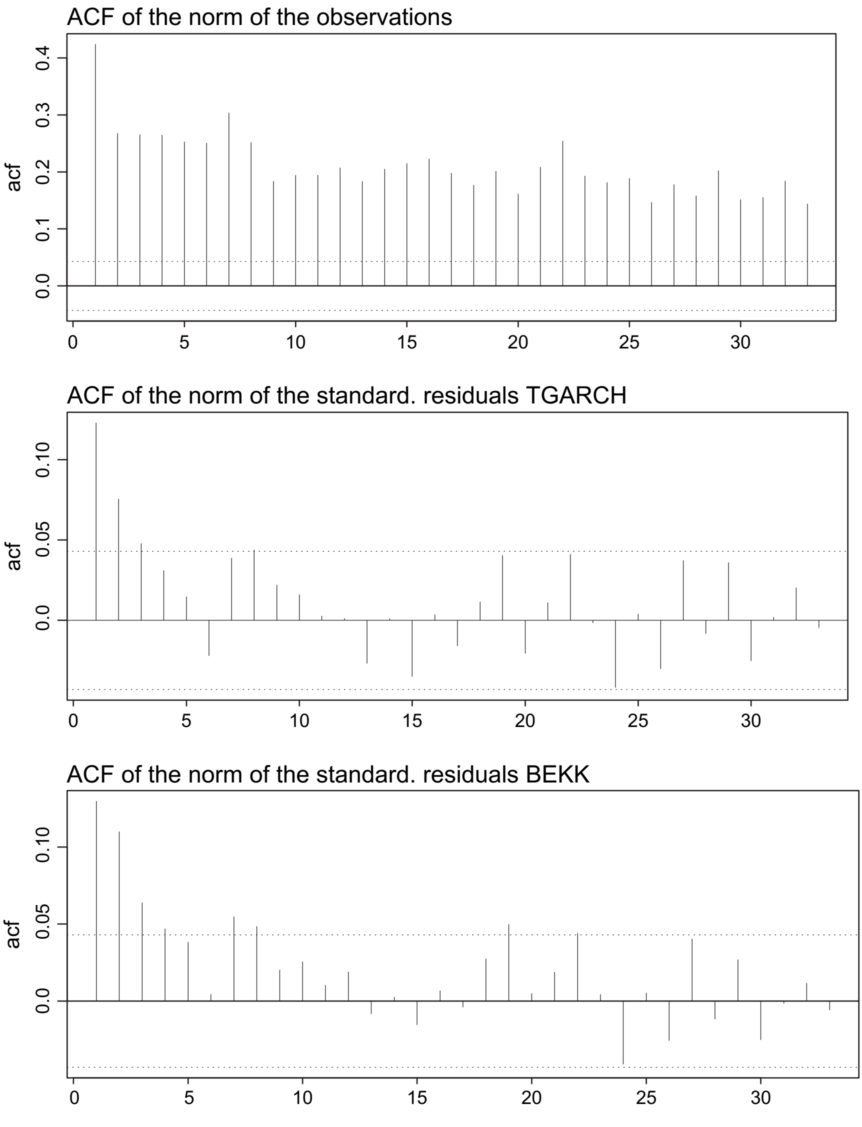

Fig. 1. AutoCorrelation functions of the norm of the observations and of the standardized residuals. *Notes*: the dotted lines identify 5% significance bands.

asymmetric volatility might well be the result of a few extreme observations such as those due to the financial crises mentioned above, and not of systematic financial behavior. In order to investigate this possibility, along with a possible change in the structure of volatility transmission, the CCC.TGARCH(1,1) model has been estimated in the pre- and post-May 1997 time periods.

The estimates of the first period, set out in the first three columns of Table 10, provide little evidence of a significant leverage effect. The conditional volatility of

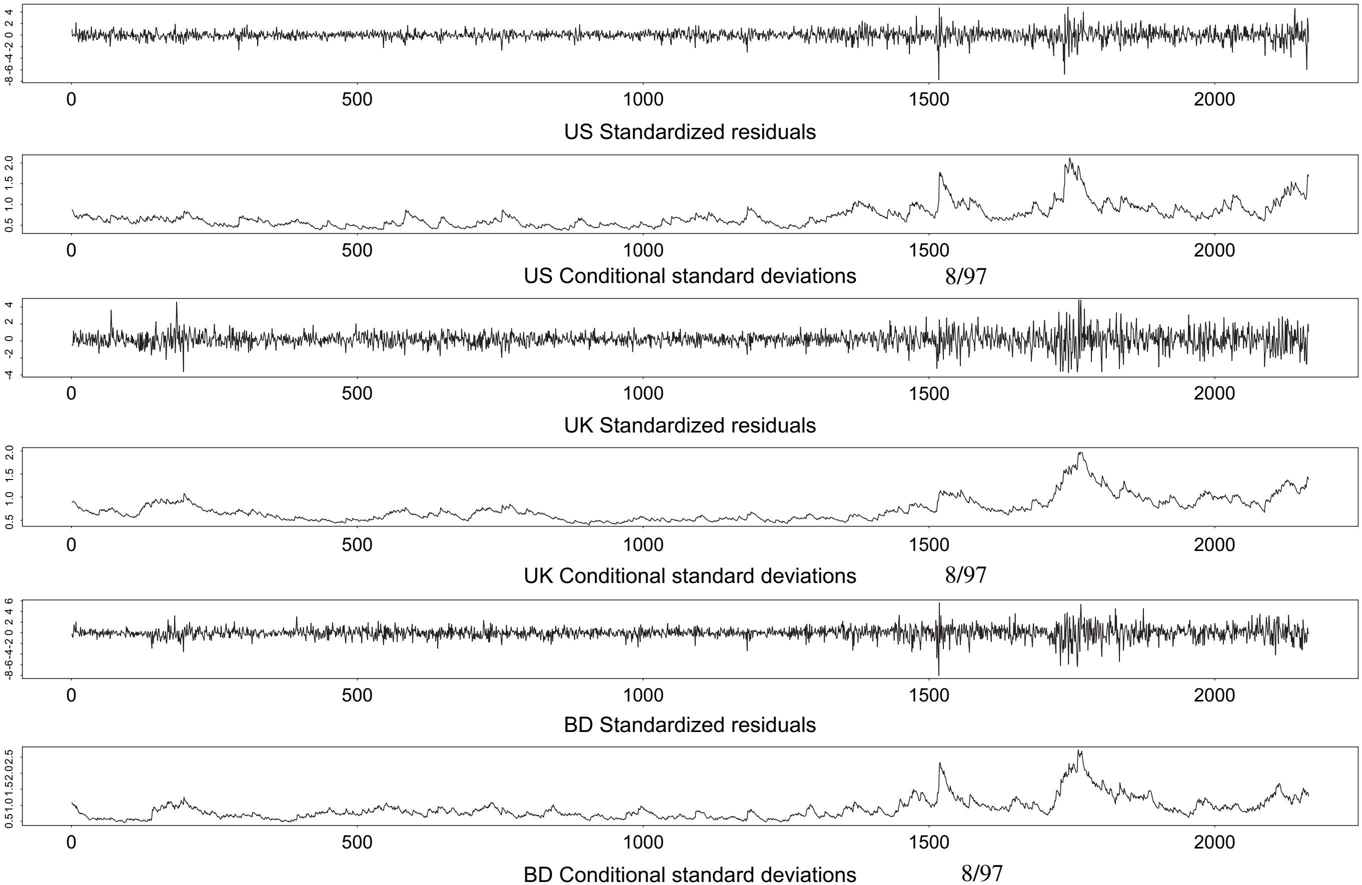

Fig. 2. Standardized residuals and conditional standard deviations of exuberance (TGARCH estimates).

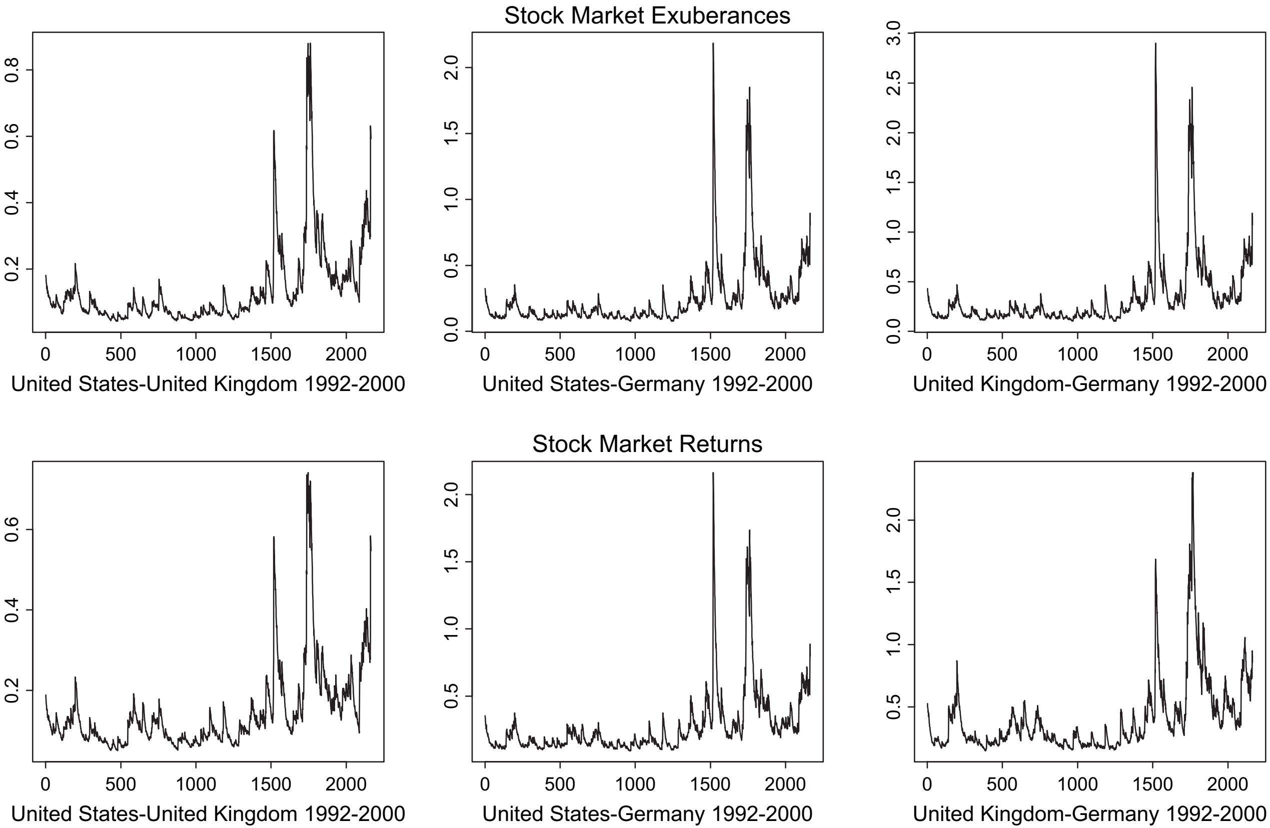

Fig. 3. Stock market conditional covariances (TGARCH estimates).

the exuberance index responds asymmetrically to past innovations in exuberance in the British market only. Conditional covariance estimates duly register the impact of the 1992 EMS crisis on stock market volatility interlinkages. As expected, the impact is greater within Europe, the conditional covariance between the British and German markets rising more than the covariances involving the US equity market (see Fig. 3). These findings suggest that the interaction between the US and European markets is, up till May 1997, rather limited.

This state of affairs sees a significant change in the second subperiod. The leverage effect is more marked and affects two out of three markets, which suggests that the outlier interpretation might be correct. The graphs in Fig. 3 show that the conditional covariances between exuberance indexes tend to be smaller—less than the corresponding return covariances—in the first subperiod, and larger in the second. Standard return volatility analysis seems to overestimate (underestimate) cross-market linkages in periods of low (high) volatility.[17] This finding implies—via straightforward algebraic manipulation of the exuberance conditional covariances—that in periods of high volatility the covariance between bond returns in two different countries is higher than the sum of the covariances between the stock return of one country and the bond return of the other. Formally, in countries j and k,

$$\mathrm{cov}_t\left(x_{\mathrm{b}j}, x_{\mathrm{b}k}\right) > \left[\mathrm{cov}_t\left(x_{\mathrm{s}j}, x_{\mathrm{b}k}\right) + \mathrm{cov}_t\left(x_{\mathrm{b}j}, x_{\mathrm{s}k}\right)\right]$$

where $x_{\mathrm{b}} = i_t + \alpha + \beta(\Delta F_{\mathrm{L}t+1}/F_{\mathrm{L}t})$, $x_{\mathrm{s}} = (\Delta s_{t+1}/s_t)$ and the exuberance is $x_{\mathrm{s}} - x_{\mathrm{b}}$. The condition holds with the opposite sign in periods of low volatility.[18] The increase in the sovereign bond return covariance during periods of turbulence is probably due to a 'flight to quality' phenomenon, which, interacting with the similarity in the issuer creditworthiness, prevents persistent interest rate divergences. On the same line

[17] We computed the differences between corresponding exuberance and return conditional covariances: they are all negative in the first subperiod and overwhelmingly positive in the second.

[18] The unconditional covariance matrices set forth below validate this hypothesis. (We use unconditional covariances as expectations of the conditional covariances converge asymptotically to unconditional ones; see Ding and Engle (1994) for the use of unconditional covariances in an analogous context.)

Unconditional variance–covariance matrices

	1/3/1992–5/30/1997						6/2/1997–4/20/2000					
	$x_{\mathrm{s\ US}}$	$x_{\mathrm{s\ UK}}$	$x_{\mathrm{s\ BD}}$	$x_{\mathrm{b\ US}}$	$x_{\mathrm{b\ UK}}$	$x_{\mathrm{b\ BD}}$	$x_{\mathrm{s\ US}}$	$x_{\mathrm{s\ UK}}$	$x_{\mathrm{s\ BD}}$	$x_{\mathrm{b\ US}}$	$x_{\mathrm{b\ UK}}$	$x_{\mathrm{b\ BD}}$
$x_{\mathrm{s\ US}}$	0.447						1.481					
$x_{\mathrm{s\ UK}}$	0.140	0.537					0.575	1.487				
$x_{\mathrm{s\ BD}}$	0.083	0.255	0.651				0.618	1.250	2.308			
$x_{\mathrm{b\ US}}$	0.044	0.024	0.004	0.028			−0.009	−0.010	−0.008	0.021		
$x_{\mathrm{b\ UK}}$	0.040	0.112	0.061	0.015	0.086		0.015	0.001	−0.007	0.015	0.052	
$x_{\mathrm{b\ BD}}$	0.033	0.073	0.062	0.014	0.044	0.056	0.011	0.004	0.007	0.016	0.038	0.054

Considering, for example, US and German assets, we find that the bond return covariances, 0.014 in the first and 0.016 in the second subperiod are, as expected, respectively, smaller than 0.037 and larger than 0.003, the sums of the stock bond return covariances. Analogous results are obtained for the remaining pairs of assets.

Table 10
CCC.TGARCH(1,1) estimates of stock exuberances (conditional t distribution)

t degree of freedom	1/3/1992–5/30/1997			6/2/1997–4/20/2000		
1992–1997 11.23 (s.e.: 1.504) 1997–2000 11.45 (s.e.: 2.163)	US ($k = 1$)	UK ($k = 2$)	BD ($k = 3$)	US ($k = 1$)	UK ($k = 2$)	BD ($k = 3$)
Variance equation						
a_0 (s.e.)	0.009 (0.00)*	0.004 (0.00)*	0.011 (0.00)*	0.079 (0.02)*	0.013 (0.01)	0.110 (0.03)*
a_1 (s.e.)	0.035 (0.01)*	0.006 (0.00)*	0.035 (0.01)*	−0.026 (0.02)	−0.028 (0.01)*	0.045 (0.02)*
a_2 (s.e.)	0.919 (0.02)*	0.958 (0.01)*	0.922 (0.02)*	0.859 (0.03)*	0.974 (0.02)*	0.847 (0.03)*
γ (s.e.)	0.008 (0.02)	0.033 (0.01)*	0.014 (0.01)	0.165 (0.03)*	0.079 (0.02)*	0.052 (0.03)
AIC		7871.82			6802.01	
BIC		7955.85			6875.99	
CCC						
ρ_{1k} (s.e.)		0.1924 (0.02)*	0.3422 (0.02)*		0.3034 (0.03)*	0.3488 (0.03)*
ρ_{2k} (s.e.)			0.3192 (0.02)*			0.6652 (0.02)*
Tests on std. residuals						
JB [prob]	105.13 [0.00]	61.40 [0.00]	86.82 [0.00]	108.27 [0.00]	6.09 [0.05]	112.3 [0.00]
BDS(2) [prob]	−1.4097 [0.16]	−0.1854 [0.93]	1.8215 [0.11]	−0.4415 [0.69]	−0.6557 [0.58]	−2.3373 [0.03]
BDS(4) [prob]	−1.2860 [0.21]	0.7125 [0.45]	2.7983 [0.01]	−1.2490 [0.23]	−0.1949 [0.89]	3.3343 [0.00]
Arch(12) [prob]	5.33 [0.94]	20.82 [0.054]	11.70 [0.47]	14.44 [0.27]	6.01 [0.91]	10.39 [0.58]

Notes: JB, Jarque Bera normality test statistic; (*), significant at the 5% level; Arch(12), Breusch Pagan test statistic for 12th order conditional heteroskedasticity; AIC, Akaike Information Criterion; BIC, Schwarz Bayesian Information Criterion; BDS(j), Brock–Dechert–Scheinkman test statistic with embedding dimension $j = 2$ and 4. The corresponding *distance* is a multiple of the standard deviation of the series.

Borio and McCauley (1996) find that bond return covariance increases may be explained by volatile inflation expectations due to monetary policy uncertainty. Cross-market correlations gain in strength and geographical scope as bond volatility rises in periods of financial stress. Bodart and Reding (1999) associate this finding also with exchange rate regime volatility and point out that the impact is stronger on bond than on stock market correlations.

Indeed, we find that, in the second subperiod, three common shocks—the Hong Kong stock market crash of October 1997, the Russian crisis following upon partial repudiation of the public debt in August 1998, and the January 1999 Brazilian exchange rate crisis—increase uncertainty and lead to higher volatility and stronger second-moment cross-market interlinkages.

King et al. (1994), and more recently Ramchand and Susmel (1998), and Baig and Goldfajn (1999) find a positive relation between market volatility and cross-market correlation. Comparison between Figs. 2 and 3 leads—prima facie—to an analogous conclusion for the three exuberance indexes under investigation. In order to assess the impact of shifts in volatility originating in a given market on the cross-market linkages of interest, a Granger causality test was performed between the squared exuberance indexes time series and the first differences of the conditional covariances produced by CCC.TGARCH(1,1) parameterization.

As shown in Table 11, the Granger causality tests indicate, for nine out of twelve cases and regardless of the subperiod, that changes in the squared stock market exuberance (i.e., in its volatility) Granger cause changes in the related conditional covariances. In the first subsample, only the US market exhibits bi-directional spillovers between volatility and covariances, whereas in the second subsample bi-directional linkages are detected between the volatility of the exuberance index in the British market and the conditional US–UK covariance. Table 12 shows *F*-statistics

Table 11
Granger causality tests between squared exuberance indexes and related first differences in conditional covariances (*F*-statistics)

	1/3/1992–5/30/1997			6/2/1997–4/20/2000		
	Lags 2	Lags 5	Lags 10	Lags 2	Lags 5	Lags 10
$(EXUS)^2 \rightarrow \Delta COV(USUK)$	60.56*	23.89*	12.48*	323*	142*	77.28*
$\Delta COV(USUK) \rightarrow (EXUS)^2$	6.14*	3.59*	1.93*	1.97	2.35	1.61
$(EXUS)^2 \rightarrow \Delta COV(USBD)$	268*	109*	53.7*	293*	135*	75.69*
$\Delta COV(USBD) \rightarrow (EXUS)^2$	4.15*	3.59*	0.73	0.02	0.56	1.02
$(EXUK)^2 \rightarrow \Delta COV(USUK)$	26.79*	11.01*	5.76*	8.14*	9.56*	5.92*
$\Delta COV(USUK) \rightarrow (EXUK)^2$	0.67	0.60	1.39	3.86*	3.55*	2.24*
$(EXUK)^2 \rightarrow \Delta COV(UKBD)$	25.43*	11.76*	6.26*	67.34*	34.64*	21.48*
$\Delta COV(UKBD) \rightarrow (EXUK)^2$	2.80	1.19	1.25	0.41	1.39	1.39
$(EXBD)^2 \rightarrow \Delta COV(USBD)$	302*	126*	62.76*	191*	116*	66.81*
$\Delta COV(USBD) \rightarrow (EXBD)^2$	0.15	1.40	0.95	2.04	3.71	1.48
$(EXBD)^2 \rightarrow \Delta COV(UKBD)$	50.38*	24.13*	12.47*	399*	251*	142*
$\Delta COV(UKBD) \rightarrow (EXBD)^2$	0.61	1.83	1.47	0.15	1.13	0.57

Note: (*) indicates rejection of the null hypothesis (no Granger causality) at the 5% significance level.

Table 12
F-statistics on the joint significance of the coefficients in the modified causality tests

	1/3/1992–5/30/1997		6/2/1997–4/20/2000	
	Value (lags)	Prob. of *F*-stat.	Value (lags)	Prob. of *F*-stat.
$(\text{EXUS})^2 \rightarrow \Delta\text{COV(USUK)}$	5.17 (6)	[0.00]	9.78 (7)	[0.00]
$\Delta\text{COV(USUK)} \rightarrow (\text{EXUS})^2$	1.90 (5)	[0.10]	4.76 (7)	[0.00]
$(\text{EXUS})^2 \rightarrow \Delta\text{COV(USBD)}$	7.29 (6)	[0.00]	8.74 (7)	[0.00]
$\Delta\text{COV(USBD)} \rightarrow (\text{EXUS})^2$	0.64 (5)	[0.66]	3.21 (7)	[0.00]
$(\text{EXUK})^2 \rightarrow \Delta\text{COV(USUK)}$	94.12 (7)	[0.00]	15.13 (5)	[0.00]
$\Delta\text{COV(USUK)} \rightarrow (\text{EXUK})^2$	0.86 (6)	[0.52]	2.85 (6)	[0.00]
$(\text{EXUK})^2 \rightarrow \Delta\text{COV(UKBD)}$	84.62 (8)	[0.00]	34.31 (7)	[0.00]
$\Delta\text{COV(UKBD)} \rightarrow (\text{EXUK})^2$	2.12 (5)	[0.06]	2.09 (5)	[0.07]
$(\text{EXBD})^2 \rightarrow \Delta\text{COV(USBD)}$	360.28 (8)	[0.00]	98.44 (8)	[0.00]
$\Delta\text{COV(USBD)} \rightarrow (\text{EXBD})^2$	0.51 (7)	[0.82]	2.04 (6)	[0.06]
$(\text{EXBD})^2 \rightarrow \Delta\text{COV(UKBD)}$	280.28 (15)	[0.00]	161.12 (9)	[0.00]
$\Delta\text{COV(UKBD)} \rightarrow (\text{EXBD})^2$	0.41 (7)	[0.89]	2.52 (5)	[0.03]

Notes: In order to avoid multicollinearity problems between the first differences of the covariances and the squared exuberance indexes the autoregressive components have been eliminated from the Granger causality test regressions, which read as follows

$$u_{jt}^2 = a_0 + \sum_{i=1}^{n} b_i \Delta\text{cov}_{jkt-i} + e_t \tag{I}$$

$$\Delta\text{cov}_{jkt} = a_0' + \sum_{i=3}^{n} b_i' u_{jt-i}^2 + e_i' \tag{II}$$

where u_{jt} is the exuberance in country j. In order to deal with an endogeneity problem, following a suggestion of the referee, the estimates of Eq. (II) are obtained dropping from the equation regressors (squared exuberance indexes) with lags 1 and 2.

from modified Granger causality regressions that account for potential endogeneity problems between the first differences of the covariances and the squared exuberance indexes. They broadly confirm the results from the unadjusted tests of Table 11.

5. Conclusion

Standard multivariate GARCH models are essentially descriptive, while economic and financial interpretations are usually superimposed a posteriori. In this paper, we introduce an ex ante structure—defining an arbitrage free stock return—and assess whether the ensuing restrictions are corroborated by the empirical evidence for three major equity markets.

Multivariate symmetric and asymmetric GARCH models are estimated in order to investigate the daily volatility in the January 1992–April 2000 period. Second-moment linkages between the US, British and German stock markets are examined using an exuberance index derived from standard portfolio arbitrage relationships. We provide a definition of exuberance, although the mechanism that may trigger it is beyond the scope of our investigation.

The main finding of the paper is that volatility transmission across countries is mostly accounted for by stock market exuberance, i.e., return covariances are de facto, exuberance covariances. Moreover, volatility modeling with exuberance indexes seems to be more accurate than modeling with stock returns.

Two subperiods are identified due to a shift in the pattern of volatility transmission in May, 1997. The successive bouts of financial turbulence occurring since May, 1997 result in an increase in the conditional second moments of the exuberance indexes and a significant rise in their covariation across markets. Market interlinkages rise in periods of uncertainty as fads and herd behavior effects loom large even in sophisticated markets. Standard return volatility analysis seems to overestimate (underestimate) cross-market linkages in periods of low (high) volatility.

However, investigation into the cross-country comovements of bonds and stocks yields ex ante information that may be of use, via analysis of exuberance indexes, in reducing portfolio risk. The introduction of exuberance indexes in dynamic portfolio hedging creates scope for further research.

Acknowledgement

The authors are grateful to Emilio Barone and especially to the anonymous referee for extremely useful and constructive suggestions. The authors remain solely responsible for any error contained herein.

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