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Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns

LORENZO CAPPIELLO
European Central Bank

ROBERT F. ENGLE
NYU Stern School of Business

KEVIN SHEPPARD
University of Oxford

ABSTRACT

This paper proposes a new generalized autoregressive conditionally heteroskedastic (GARCH) process, the asymmetric generalized dynamic conditional correlation (AG-DCC) model. The AG-DCC process extends previous specifications along two dimensions: it allows for series-specific news impact and smoothing parameters and permits conditional asymmetries in correlation dynamics. The AG-DCC specification is well suited to examine correlation dynamics among different asset classes and investigate the presence of asymmetric responses in conditional variances and correlations to negative returns. We employ the AG-DCC model to analyze the behavior of international equities and government bonds. While equity returns show strong evidence of asymmetries in conditional volatility, little is found for bond returns. However, both equities *and* bonds exhibit asymmetries in conditional correlations, with equities responding stronger than bonds to joint bad news. The article also finds that, during periods of financial turmoil, equity market volatilities show important linkages, and conditional equity correlations among regional groups increase dramatically. Furthermore, in January 1999 with the introduction of the euro, we document significant evidence of a structural break in correlation although *not* in

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volatility. The introduction of a fixed exchange rate regime leads to near-perfect correlation among bond returns within the European Monetary Union (EMU) countries, which is not surprising when considering the harmonization in monetary policy. However, the increase in return correlation is not restricted to bond returns in EMU countries: equity return correlation both within and outside the EMU also increases.

KEYWORDS: dynamic conditional correlation, international stock and bond correlation, multivariate GARCH, variance targeting

Most financial decisions involve a trade-off between future risks and asset returns. The volatilities and correlations of securities are often the major components of risk. Second moments evolve over time as the economy changes and new information is released. Volatilities and correlations measured from historical data may miss changes in risk unless the methods are carefully designed to update estimates rapidly.

This article develops an econometric technique to measure risks dynamically by finding the optimal time decay of covariance information. The method is employed to investigate conditional asymmetries in volatilities and correlations for a collection of global equity and bond indices. We investigate whether all correlations and volatilities show this asymmetry and how similar are the patterns of correlations across the globe. To model the covariance structure of world investment markets, we compute returns using the Financial Times All-World equity and DataStream-constructed constant maturity bond indices.

Over the past 20 years, a large literature has developed exploring the second moment dynamics of assets' returns. Among other regularities, (conditional) estimates of the second moment of equities often exhibit the so-called asymmetric volatility phenomenon, where volatility increases more after a negative than after a positive shock of the same magnitude. Surprisingly, while there has been a proliferation of conditional econometric models capable of capturing asymmetry in conditional volatilities [see Hentschel (1995) for an exposition], econometric specifications that explicitly model asymmetry in conditional covariances and, specifically, conditional correlations are far less common. There exist studies that account for asymmetric effects in conditional covariances [see, for instance, Koutmos and Booth (1995), Booth, Martikainen, and Tse (1997), Scruggs (1998), and Christiansen (2000)], although they parameterize time-varying covariances in the spirit of Bollerslev (1990) where correlation coefficients are assumed to be constant over the sample period. Although assuming constant correlation greatly simplifies estimation, this hypothesis is neither theoretically justified nor robust to the empirical evidence.

A more flexible class of multivariate conditional variance models, without the assumption of constant correlation coefficients and with explicit asymmetry in conditional variances *as well as* covariances, has been introduced by Kroner and

Ng (1998). Subsequent applications [see, for instance, Bekaert and Wu (2000) and Scruggs and Glabadanidis (2003)] build on this model. As with most multivariate generalized autoregressive conditionally heteroskedastic (GARCH) models, these specifications suffer from the curse of dimensionality, which limits their scope for application.

The second stylized fact that emerges from surveying empirical research is that while the asymmetric phenomenon in conditional variances has been widely explored for individual stocks, equity portfolios, and stock market indices, day-to-day changes in government bond return volatility has received little attention [one exception is, inter alia, Scruggs and Glabadanidis (2003)]. Research, instead, has focused on the impacts of macroeconomic news announcements on conditional volatility of bonds and Treasury bills [see, for instance, Jones, Lamont and Lumsdaine (1998), Li and Engle (1998), and Christiansen (2000)].[1]

The goals of this article are threefold. First, we develop a model capable of allowing for conditional asymmetries not only in volatilities but also in correlations. We propose a generalization of the dynamic conditional correlation (DCC) GARCH model of Engle (2002). We extend the original model along two dimensions: on the one hand, we allow for series-specific news impact and smoothing parameters and, on the other hand, permit conditional asymmetries in correlations. The univariate volatility parameterizations are also modified from standard GARCH(1,1) models to accommodate conditional asymmetries. The combination of these two approaches results in a specification that is flexible and yet feasible for many assets. The second goal is to investigate whether, in addition to stocks, government fixed-income securities *also* exhibit asymmetry in conditional second moments, either in conditional volatilities or in correlations. Finally, using a broad cross section of national equity market indices and government fixed-income portfolios, this article explores the dynamics and changes in the correlation of these asset markets. Unlike previous research, we will not investigate whether conditional second moments of fixed-income securities change when (macroeconomics) news are released. We will test, instead, whether conditional variances, covariances, and correlations of such assets are sensitive to the sign of past innovations. We also explore the asymmetric volatility impact of an innovation through the "news impact curves" of Engle and Ng (1993) and asymmetry in conditional covariances and correlations using "news impact surfaces" of Kroner and Ng (1998).

Within our framework, a number of questions can be addressed. Has the formation of the monetary union in Europe increased the correlation among national assets? If this is the case, should the euro area be considered a unified financial block and might the investors move capital, which before was allocated within the euro area, towards other regions? Moreover, what are the consequences of growing asset correlation, if any, on international portfolio diversification? Is diversification actually present when it is most needed? Is it available

[1] In fact, little has been done to explore the correlation structure of bond returns across countries.

when markets are highly volatile? Are the linkages stronger at the regional level than they are at the global level? Has the overall return correlation of both bonds and equities increased over second half of the 1990s and into the early years of the new millennium, as evidenced in Moskowitz (2003)?

The article is laid out as follows: the next section summarizes the explanations proffered to justify the asymmetric volatility phenomenon. Section 2 discusses the econometric specification and Section 3 describes the data employed in the analysis. Section 4 presents the multivariate conditional covariance results and provides a discussion about the linkages between volatility series, correlation series, and across volatility and correlation series. Section 5 concludes and proposes areas for further research.

1 WHY CONDITIONAL ASYMMETRIES?

Economically, two theories exist to explain asymmetric volatility: the leverage effect and time-varying risk premia (volatility feedback). The leverage effect, due to Black (1976) and Christie (1982), states that after an unexpected drop in a stock value, the debt-to-equity ratio of a firm increases. Thus, the volatility of the whole firm, which is assumed to remain constant, must be reflected by an increase in volatility in the nonleveraged part of the firm (equity). An alternative explanation of the larger increase in volatility after a negative shock was originally proposed by French, Schwert, and Stambaugh (1987) and further developed by Campbell and Hentschel (1992) and Wu (2001). News that volatility will be higher in the future will induce risk-adverse investors to sell positions today until the expected return rises to compensate for the risk. Hence, markets decline in advance of volatility increases. A related claim is that after a negative return shock and variance increase, the required rise in expected return creates more volatility (volatility feedback). The arguments based on risk aversion are only sensible for systematic risks. These explanations for asymmetries in volatility are not exclusive. Bekaert and Wu (2000) combine them in an empirical model and show that the leverage effect *alone* does not adequately explain the changes in volatility after a decrease in the asset price.

Both the leverage effect and the volatility feedback hypothesis have primarily focused on the volatility of equities. Nevertheless, through the capital asset pricing model (CAPM), treating bonds as risky assets [see, for instance Bollerslev, Engle, and Wooldrige (1988)], the model developed by Campbell and Hentschel (1992) is applicable not only to stocks but also to bonds. As for the leverage effect, it cannot apply for government bonds, as they do not have leverage.

In addition to possible explanations for asymmetries in return volatility, little theoretical framework is available to justify the recent evidence of asymmetric response to joint bad news in correlations.[2] One possible explanation rests on time-varying risk premia. More precisely, a negative systematic shock will induce

[2] In this context, joint bad news refer to both returns being negative.

downward pressure on returns in any pair of stocks and will increase the variances of these securities in a CAPM-type world. If betas do not change, then covariances will increase. If idiosyncratic variances do not proportionally change, correlations will increase as well. Correlation may therefore be higher after a negative innovation than after a positive innovation of the same magnitude.

2 ECONOMETRIC METHODOLOGY

To investigate the properties of international equity and bond returns, we generalize the DCC GARCH model of Engle (2002) by introducing two modifications: asset-specific correlation evolution parameters and conditional asymmetries in correlation.

Let r_t be a $k \times 1$ vector of asset returns, which is assumed to be conditionally normal with mean zero and covariance matrix H_t:

$$r_t|\Im_{t-1} \sim N(0, H_t), \tag{1}$$

where $\Im_{t-1}$ is the time $t-1$ information set. All DCC class models [including the constant conditional correlation (CCC) GARCH of Bollerslev (1990)] use the fact that H_t can be decomposed as follows:

$$H_t = D_t P_t D_t. \tag{2}$$

D_t is the $k \times k$ diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{it}}$ on the ith diagonal, and P_t is the (possibly) time-varying correlation matrix. As the DCC model is designed to allow for three-stage estimation of the conditional covariance matrix, any univariate GARCH process that is covariance stationary and assumes normally distributed errors (irrespective of the true error distribution) can be used to model the variances [see Engle and Sheppard (2001) for further details].[3] In the first stage, univariate volatility models are fit for each of the assets, and estimates of h_{it} are obtained. In the second stage, asset returns, transformed by their estimated standard deviations, are used to estimate the intercept parameters of the conditional correlation. Finally, the third stage conditions on the correlation intercept parameters to estimate the coefficients governing the dynamics of correlation. In the original DCC estimator, the correlation evolves according to a process with identical news impact and smoothing parameters for all pairs of variables. However, for high-dimensional models, this assumption is very strong and we propose the asymmetric generalized DCC (AG-DCC) estimator to better capture the heterogeneity present in the data.

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[3] The assumption of conditional normality is not crucial, and in its absence, the results have a standard quasi maximum likelihood estimation (QMLE) interpretation.

The three-stage estimation procedure is computationally convenient but may be inefficient relative to a maximum likelihood estimation of all the parameters at once. The efficiency of the three-stage estimation process has been studied asymptotically in Engle and Sheppard (2005) and in simulations in Engle and Sheppard (2001). They compared estimated univariate models with exact knowledge of the univariate parameters and found that the estimation of the univariate models has little consequence. A similar examination of the correlation process shows that separate estimation of the intercept and dynamic parameters introduces a small finite sample bias relative to exact knowledge of the unconditional correlation matrix. The bias was increasing in the cross-section size of the data set and with $k = 25$ was small.

These results, however, all assume that the model is correctly specified. If the univariate models are not well specified, then the correlation estimates will no longer be consistent. As the choice of univariate model will not affect the sign of the standardized residuals and as many univariate models produce relatively similar volatility patterns, it is possible that the correlations would be relatively insensitive to the univariate model at least within a reasonable class. Rather than rely on this intuition, we carry out an extensive model selection procedure for the univariate models to minimize the risk that the univariate models will lead to inconsistent correlation estimates.

Univariate volatility specifications are selected using the Bayesian information criterion (BIC) from a class of models capable of capturing the common features of financial asset return variance.[4] We include the following models in the specification search (all with one lag of the innovation and one lag of volatility):

1. GARCH [Bollerslev (1986)]
2. AVGARCH [Taylor (1986)]
3. NARCH [Higgins and Bera (1992)]
4. EGARCH [Nelson (1991)]
5. ZARCH [Zakoian (1994)]
6. GJR-GARCH [Glosten, Jagannathan, and Runkle (1993)]
7. APARCH [Ding, Engle, and Granger (1993)]
8. AGARCH [Engle (1990)]
9. NAGARCH [Engle and Ng (1993)].

Appendix A.1 contains the exact specifications employed for these processes.

[4] Although there are many information criteria available, in addition to likelihood ratio tests using nested models, the use of the BIC is appropriate as it leads to the correct model specification being selected asymptotically as long as it is a member of the group. The BIC was computed as $-2LL + N\ln(T)$ where LL is the maximized log likelihood and N is the number of parameters in the specification.

Once the univariate volatility models are estimated, the standardized residuals, $\varepsilon_{it} = r_{it}/\sqrt{h_{it}}$, are used to estimate the correlation parameters. The evolution of the correlation in the standard DCC model [Engle (2002)] is given by

$$Q_t = (1 - a - b)\bar{P} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1}, \tag{3}$$

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{4}$$

where $\bar{P} = E[\varepsilon_t \varepsilon'_t]$ and a and b are scalars such that $a + b < 1$. $Q_t^* = [q_{iit}^*] = \left\lfloor \sqrt{q_{iit}} \right\rfloor$ is a diagonal matrix with the square root of the ith diagonal element of Q_t on its ith diagonal position. As long as Q_t is positive definite, Q_t^* is a matrix which guarantees $P_t = Q_t^{*-1} Q_t Q_t^{*-1}$ is a correlation matrix with ones on the diagonal and every other element ≤ 1 in absolute value. The model described by Equations (3) and (4), however, does not allow for asset-specific news and smoothing parameters or asymmetries.

We propose to modify the correlation evolution equation to be

$$\begin{aligned} Q_t = {} & (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'n_{t-1}n'_{t-1}G \\ & + B'Q_{t-1}B, \end{aligned} \tag{5}$$

where A, B, and G are $k \times k$ parameter matrices, $n_t = I[\varepsilon_t < 0] \circ \varepsilon_t$ ($I[\cdot]$ is a $k \times 1$ indicator function which takes on value 1 if the argument is true and 0 otherwise, while "$\circ$" indicates the Hadamard product) and $\bar{N} = E[n_t n'_t]$. We refer to the model in Equation (5) as the AG-DCC. The asymmetric DCC (A-DCC) is obtained as a special case of the AG-DCC if the matrices A, B, and G are replaced by scalars. Similarly, the generalized DCC (G-DCC) is a special case of the AG-DCC when $G = 0$. For $\bar{P}$ and $\bar{N}$, expectations are infeasible and are replaced with sample analogues, $T^{-1}\sum_{t=1}^{T} \varepsilon_t \varepsilon'_t$ and $T^{-1}\sum_{t=1}^{T} n_t n'_t$, respectively.

It is clear from Equation (5) that a sufficient condition for Q_t to be positive definite for all possible realizations is that the intercept, $\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G$, is positive semi-definite and the initial covariance matrix Q_0 is positive definite [see Ding and Engle (2001) for further details]. In the scalar symmetric DCC model, the condition is simply $a^2 + b^2 < 1$. In the scalar A-DCC model,

$$Q_t = \left(\bar{P} - a^2\bar{P} - b^2\bar{P} - g^2\bar{N}\right) + a^2\varepsilon_{t-1}\varepsilon'_{t-1} + g^2 n_{t-1}n'_{t-1} + b^2 Q_{t-1}, \tag{6}$$

a sufficient condition for Q_t to be positive definite is that the matrix in parentheses is positive semi-definite. A necessary and sufficient condition for this to hold is

$$a^2 + b^2 + \delta g^2 < 1, \tag{7}$$

where δ = maximum eigenvalue $[\bar{P}^{-1/2}\bar{N}\bar{P}^{-1/2}]$.[5]

This constraint can be evaluated on the sample data and implemented during estimation of the conditional correlation. As a consequence, estimation of the scalar A-DCC is no more difficult than the scalar DCC.

If the matrices A, B, and G are assumed to be diagonal, the AG-DCC representation reduces to

$$Q_t = \bar{P} \circ (ii' - aa' - bb') - \bar{N} \circ gg' + aa' \circ \varepsilon_{t-1}\varepsilon_{t-1}' + gg' \circ n_{t-1}n_{t-1}' + bb' \circ Q_{t-1}, \tag{8}$$

where i is a vector of ones and a, b, and g are vectors containing the diagonal elements of the matrices A, B, and G, respectively. In this case, a sufficient condition for Q_t to be positive definite for all t is that the intercept, $\bar{P} \circ (ii' - aa' - bb') - \bar{N} \circ gg'$, is positive semi-definite and the matrix Q_0 is positive definite.

The AG-DCC generalization comes at the cost of added parameters and complexity. The generalized models require k^2 parameters in each correlation term, although we use diagonal versions with only k additional coefficients in each term. In the diagonal specification, the number of unknown parameters grows linearly with the number of assets.

Although the diagonal versions are appropriate for applications to many assets, the scalar specifications are preferred when the number of assets is very large. For example, when k = 50, the scalar versions require the simultaneous estimation of two or three parameters, depending on whether the symmetric or asymmetric specification is used. The diagonal parameterizations, instead, imply 100 or 150 unknown coefficients, depending on whether asymmetries are included. The inversion, at each point in time, of the conditional correlation matrix is the fundamental limitation of the diagonal (asymmetric) DCC GARCH model. Various specifications for modeling the conditional covariance of large systems have recently been explored in Engle and Sheppard (2005). They document that DCC-family models, even using standard univariate GARCH specifications, offer the best performance among the families which are applicable to large panels.

It is simple to further extend the model to allow for structural breaks in mean, in dynamics, or in both. Let d_t be a dummy variable which takes on value 1, if $t \geq \tau < T$ and 0 otherwise. Then assume that, for example, the researcher is interested in examining whether a structural break has occurred in the intercept. In this case, the following model can be tested:

[5] The coefficients are squared to ensure consistency with the AG-DCC model. However, nonnegative constraints on the coefficients can be imposed using any method.

$$\begin{aligned} Q_t = {} & (\bar{P}_1 - A'\bar{P}_1 A - B'\bar{P}_1 B - G'\bar{N}_1 G)(1 - d_t) \\ & + (\bar{P}_2 - A'\bar{P}_2 A - B'\bar{P}_2 B - G'\bar{N}_2 G)d_t + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'n_{t-1}n'_{t-1}G \\ & + B'Q_{t-1}B, \end{aligned} \tag{9}$$

where $\bar{P}_1 = E\left[\varepsilon_t\varepsilon'_t\right]$, $t < \tau$, and $\bar{P}_2 = E\left[\varepsilon_t\varepsilon'_t\right]$, $t \geq \tau$, with $\bar{N}_1$ and $\bar{N}_2$ analogously defined.

As the model in Equation (9) nests the model in Equation (5), it is straightforward to test for breaks in the mean of the process. The test can be conducted using likelihood ratio or Wald tests with $k(k-1)/2$ degrees of freedom. Breaks in dynamics as well as in both dynamics and mean can be tested for analogously, although the degrees of freedom will be different.

Kroner and Ng (1998) introduced news impact surfaces for multivariate GARCH models, which are analogous to news impact curves for univariate processes. For the model considered in this article, the news impact surface for correlation will be asymmetric, having (potentially) greater response to joint bad news than to joint good news. The news impact surface for correlation is given by

$$\begin{aligned} & f\left(\varepsilon_i, \varepsilon_j\right) \approx \tilde{c}_{ij} + \left(a_i a_j + g_i g_j\right)\varepsilon_i\varepsilon_j, && \text{for } \varepsilon_i, \varepsilon_j < 0, \\ & f\left(\varepsilon_i, \varepsilon_j\right) \approx \tilde{c}_{ij} + a_i a_j \varepsilon_i \varepsilon_j, && \text{otherwise,} \end{aligned} \tag{10}$$

where ε_i and ε_j are standardized residuals.[6] The news impact surface for covariance will simply be the news impact surface for correlations multiplied by the appropriate portion of the news impact curve for the univariate models. Considering the wide range of univariate specifications for the conditional variances, the covariance impact surfaces can be very different should the chosen models for the univariate volatilities be drastically different, producing asymmetries in covariance in all four directions from the origin.

3 DATA

The data employed for this article consist of FTSE All-World Indices for 21 countries and DataStream-constructed five-year average maturity government bond indices for 13. Equity indices include European countries (Austria, Belgium, Denmark, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom), Australasia (Australia, Hong Kong, Japan, New Zealand, and Singapore), and the Americas (Canada, Mexico, and the United States). Data on government bonds are available for all the European countries

[6] This formula is approximate, due to the nonlinear transformation needed. The exact news impact surface is given in Appendix A.2.

listed above (except Italy, Norway, and Spain), Japan, Canada, and the United States.[7] The FTSE All-World Index Series measure the return on a well-diversified investment, are value-weighted, and include dividends. The DataStream Benchmark bond indices consist of the most liquid government bonds and follow the European Federation of Financial Analysts (EFFAS) methodology. Given the global scope for this article, there is never a time when all 21 markets are open. To alleviate the resulting nonsynchronous trading issues, we use returns at weekly frequency. The sample covers the period from January 8, 1987 until February 7, 2002, a total of 785 observations. All returns were continuously compounded using Thursday-to-Thursday closing prices to avoid any end-of-week effects.

Table 1 contains descriptive statistics for the data which exhibit the standard properties of financial returns. All markets, except New Zealand and Japan, exhibit an average positive return. As for equity returns, all (but two) are left skewed and exhibit fat-tails. As expected, when we standardize returns with their preferred standard deviation (see Section 4), they are both less skewed and less fat-tailed, although still nonnormal as shown by the Jarque–Bera test. Bond index returns are more homogeneous, with annualized returns ranging from 4.35 to 8.74, have a global mean of 6.68, and have uniformly lower standard deviations than the least volatile equity index. Nine of 13 bond index return series are positively skewed, and all are leptokurtotic. The standardized bond index returns are also slightly less skewed and less fat-tailed. As was the case with equity returns, bond index returns typically reject the null of normality.

Table 2 summarizes information about the distribution of the unconditional correlations between the equity series, the bond series, as well as the equity and the bond indices, and Tables 3a, 3b, and 3c report the unconditional correlations for each of the 34 assets. Overall, the assets are moderately correlated with a median unconditional correlation of 0.299. Correlation is higher for asset in the same class. The median bond–bond and equity–equity return correlations are equal to 0.728 and 0.444, respectively, while the median equity–bond correlation is only 0.185. Each of these three median correlations is statistically different from the other two at the 1% level.[8] The intraequity return correlations increase when considered at the regional level. Correlations between bond indices also suggest the presence of three distinct groups.

Finally, we investigate nonparametrically the presence of asymmetries in conditional second moments (see Table 4). First, we examine whether the variances of asset returns are higher after a negative than after a positive shock of the

[7] The 13 national bonds which we consider in the analysis are a proper subset of the 21 equity markets and include all the major world government bond markets.

[8] Although the distribution of the average correlation for groups of assets is difficult to calculate, we are able to conduct significance test using the bootstrap distributions of these statistics. The bootstrap distribution was tabulated using the stationary bootstrap [Politis and Romano (1994)] with an average window length of 13 weeks (based on initial estimates of the persistence of correlation across all assets). When statistical significance is detected, it means that the empirical quantile of the bootstrap distribution is less than (or greater than, depending on the test) the statistic.

Table 1 Descriptive statistics.

	Mean[a]	Standard deviation[a]	Skewness	Kurtosis	Standardized skewness	Standardized kurtosis
Australia stocks	9.10	20.49	−2.23	24.33	−1.26	12.25
Austria stocks	4.76	20.74	−0.22	5.57	−0.24	4.49
Belgium stocks	9.98	18.24	−0.38	6.65	−0.50	4.76
Canada stocks	7.96	17.57	−0.78	8.68	−0.48	5.50
Denmark stocks	11.36	18.28	−0.07	5.22	−0.12	4.25
France stocks	9.95	19.15	−0.21	4.37	−0.21	3.25
Germany stocks	6.75	21.10	−0.43	5.36	−0.57	4.53
Hong Kong stocks	11.35	28.93	−2.25	23.73	−0.47	5.10
Ireland stocks	11.12	21.67	−0.71	7.37	−0.37	5.15
Italy stocks	3.14	24.62	0.10	5.48	−0.07	4.00
Japan stocks	−0.74	23.68	0.17	4.41	−0.03	4.03
Mexico stocks	21.23	40.33	−0.71	8.15	−0.23	4.47
Netherlands stocks	12.21	17.42	−0.54	7.81	−0.63	4.11
New Zealand stocks	−0.08	23.26	−0.55	6.88	−0.31	5.73
Norway stocks	7.43	23.57	−0.75	8.04	−0.79	8.36
Singapore stocks	7.00	29.70	−1.91	23.47	−1.33	15.41
Spain stocks	9.46	21.89	−0.25	5.76	−0.11	3.92
Sweden stocks	11.89	24.67	−0.27	6.31	−0.28	4.21
Switzerland stocks	9.33	19.07	−0.44	8.27	−0.60	7.15
U.K. stocks	10.99	17.59	−1.07	15.24	−1.06	12.01
U.S. stocks	12.29	15.90	−0.84	7.56	−0.53	4.10
Austria bonds	5.83	11.13	0.21	3.88	0.24	3.43
Belgium bonds	6.70	11.14	0.35	3.72	0.35	3.52
Canada bonds	7.33	7.78	−0.07	3.58	−0.09	3.45**
Denmark bonds	8.08	11.12	0.23	3.93	0.22	3.65
France bonds	6.69	10.91	0.36	3.91	0.33	3.42**
Germany bonds	5.17	11.23	0.28	3.66	0.29	3.35
Ireland bonds	8.10	11.36	−0.08	3.85	−0.07	3.35*
Japan bonds	6.33	12.74	1.00	8.84	0.70	4.98
Netherlands bonds	5.64	11.22	0.27	3.76	0.26	3.36
Sweden bonds	6.95	11.50	−0.29	4.30	−0.24	3.64
Switzerland bonds	4.35	12.55	0.16	3.69	0.24	3.42
U.K. bonds	8.74	10.97	−0.03	4.54	−0.08	3.96
U.S. bonds	6.94	4.55	0.43	8.72	0.08	5.18

This table reports summary statistics for the 21 Equity Index returns and 13 Bond Index returns. The standardized skewness and kurtosis are the skewness and kurtosis of the returns standardized by their estimated standard deviation.
[a]Annualized percent.
* and ** denote standardized residuals insignificantly different from a normal distribution at 5% and 1% level, respectively.

Table 2 Average correlations.

Equity indices			
	Mean	Minimum	Maximum
	0.4170	0.2783	0.5334
	Australasia	Europe	North America
Australasia	0.4075	0.3381	0.3142
Europe		0.5296	0.3608
North America			0.4735
Bond indices			
	Mean	Minimum	Maximum
	0.5684	0.1457	0.7193
	Australasia	Europe	North America
Australasia	N/A	0.4302	0.0624
Europe		0.8034	0.1667
North America			0.4195
Bond and equity indices			
	Mean	Minimum	Maximum
	0.1442	−0.0535	0.2377
		Bonds	
Equities	Australasia	Europe	North America
Australasia	0.1316	0.0546	−0.0241
Europe	0.1054	0.2731	0.0455
North America	−0.0572	−0.0740	0.0903

This table reports summary statistics for the 21 equity index returns and 13 bond index returns correlations, grouped by region. The numbers in the matrices are the average correlation between the appropriate groups, that is, in the last section, the upper left element is the average correlation between Australasian equity returns and Australasian bond returns. In the top two panels, the diagonal numbers are the within-group average correlation for equity and bond returns. There is no within-group correlation for Australasian bond portfolios, as Japanese bonds were the only asset in the Australasian bond category.

same magnitude. We calculate the $E\lfloor r_{it}^2 | r_{it-1} < 0 \rfloor$ and test the null that $E\lfloor r_{it}^2 | r_{it-1} < 0 \rfloor = E\lfloor r_{it}^2 | r_{it-1} > 0 \rfloor$ by regressing squared returns on a constant and an indicator function for negative lagged returns. Nineteen of the equity indices exhibit larger variances after a negative than after a positive shock, and 11 of these differences were significant at a 10% level. As for the bond indices, nine of them show larger variances after negative shocks, although only one was significantly different from zero. Following the same line of analysis, we investigate whether the average covariances are different after joint negative returns than after two positive returns. We define an indicator function for both past returns being negative and another for both being positive. By regressing the return cross product on a constant and the two indicators, we test the hypothesis

Table 3a Unconditional correlations between equity returns.

	Austria	Belgium	Canada	Denmark	France	Germany	Hong Kong	Ireland	Italy	Japan	Mexico	The Netherlands	New Zealand	Norway	Singapore	Spain	Sweden	Switzerland	United Kingdom	United States
Australia	0.269	0.362	0.430	0.244	0.389	0.379	0.452	0.417	0.292	0.282	0.292	0.449	0.629	0.438	0.466	0.404	0.427	0.420	0.493	0.333
Austria		0.516	0.177	0.386	0.439	0.576	0.237	0.378	0.339	0.260	0.153	0.477	0.280	0.391	0.315	0.433	0.338	0.497	0.359	0.169
Belgium			0.281	0.515	0.611	0.651	0.322	0.499	0.444	0.295	0.194	0.669	0.323	0.423	0.366	0.588	0.463	0.642	0.479	0.299
Canada				0.279	0.462	0.399	0.316	0.361	0.320	0.230	0.304	0.493	0.341	0.433	0.388	0.378	0.497	0.391	0.463	0.692
Denmark					0.496	0.550	0.244	0.449	0.471	0.288	0.181	0.545	0.204	0.443	0.276	0.498	0.478	0.521	0.460	0.299
France						0.729	0.347	0.486	0.537	0.340	0.258	0.709	0.319	0.453	0.382	0.630	0.577	0.641	0.594	0.465
Germany							0.370	0.515	0.543	0.321	0.268	0.769	0.336	0.524	0.406	0.624	0.639	0.722	0.562	0.432
Hong Kong								0.363	0.269	0.229	0.294	0.365	0.365	0.321	0.601	0.401	0.394	0.318	0.396	0.308
Ireland									0.402	0.279	0.208	0.572	0.313	0.493	0.427	0.510	0.474	0.528	0.634	0.392
Italy										0.237	0.236	0.521	0.263	0.370	0.279	0.526	0.501	0.453	0.443	0.329
Japan											0.148	0.337	0.265	0.258	0.346	0.304	0.317	0.343	0.350	0.223
Mexico												0.293	0.270	0.248	0.309	0.322	0.333	0.236	0.280	0.381
The Netherlands													0.375	0.573	0.436	0.612	0.600	0.729	0.663	0.522
New Zealand														0.354	0.397	0.379	0.358	0.336	0.381	0.290
Norway															0.401	0.470	0.537	0.503	0.487	0.367
Singapore																0.409	0.395	0.405	0.468	0.396
Spain																	0.591	0.572	0.540	0.403
Sweden																		0.549	0.539	0.490
Switzerland																			0.585	0.398
United Kingdom																				0.495

This table reports unconditional correlations of equity returns.

Table 3b Unconditional correlations between equity and bond returns.

	Austria	Belgium	Canada	Denmark	France	Germany	Ireland	Japan	The Netherlands	Sweden	Switzerland	United Kingdom	United States
Australia	0.022	0.028	0.118	0.042	0.009	0.006	0.065	0.023	−0.001	0.145	−0.036	0.055	−0.165
Austria	0.391	0.364	0.059	0.346	0.353	0.372	0.329	0.161	0.371	0.277	0.268	0.198	0.035
Belgium	0.435	0.468	0.125	0.455	0.451	0.448	0.406	0.187	0.446	0.410	0.319	0.289	0.051
Canada	−0.083	−0.076	0.383	−0.065	−0.101	−0.091	−0.038	−0.052	−0.087	0.083	−0.141	−0.037	−0.039
Denmark	0.419	0.432	0.083	0.532	0.438	0.427	0.425	0.160	0.435	0.425	0.338	0.338	0.044
France	0.270	0.297	0.149	0.316	0.347	0.292	0.299	0.157	0.291	0.356	0.171	0.239	0.009
Germany	0.323	0.336	0.076	0.342	0.327	0.358	0.321	0.139	0.352	0.371	0.203	0.206	−0.035
Hong Kong	−0.030	−0.007	0.067	0.012	−0.013	−0.037	0.009	0.055	−0.041	0.083	−0.096	0.000	−0.078
Ireland	0.219	0.226	0.111	0.254	0.213	0.207	0.299	0.045	0.207	0.252	0.104	0.225	−0.014
Italy	0.157	0.177	0.121	0.222	0.184	0.155	0.203	0.027	0.157	0.295	0.052	0.172	−0.023
Japan	0.188	0.202	0.032	0.200	0.163	0.202	0.170	0.530	0.195	0.181	0.178	0.181	−0.062
Mexico	−0.059	−0.067	0.111	−0.031	−0.038	−0.075	−0.034	−0.053	−0.064	0.046	−0.091	−0.037	−0.037
The Netherlands	0.305	0.311	0.125	0.319	0.293	0.314	0.283	0.139	0.319	0.347	0.204	0.214	−0.042
New Zealand	0.029	0.057	0.057	0.048	0.024	0.025	0.040	0.038	0.020	0.146	−0.029	0.047	−0.144
Norway	0.184	0.170	0.064	0.198	0.159	0.179	0.186	0.041	0.181	0.247	0.089	0.115	−0.129
Singapore	0.023	0.036	0.015	0.052	0.000	0.011	0.059	0.081	0.007	0.113	−0.034	0.010	−0.171
Spain	0.252	0.270	0.116	0.311	0.284	0.250	0.269	0.066	0.261	0.332	0.135	0.201	−0.033
Sweden	0.158	0.167	0.127	0.201	0.162	0.166	0.194	0.053	0.167	0.429	0.066	0.162	−0.078
Switzerland	0.349	0.374	0.062	0.381	0.360	0.377	0.341	0.201	0.375	0.382	0.351	0.240	−0.017
United Kingdom	0.195	0.212	0.147	0.239	0.195	0.197	0.269	0.124	0.190	0.286	0.117	0.435	−0.049
United States	−0.084	−0.078	0.174	−0.057	−0.097	−0.084	−0.050	−0.090	−0.084	0.067	−0.176	−0.053	−0.081

This table reports unconditional correlations of returns across the equity (down) and bond markets (across). For instance, the upper left entry is the correlation between Australian equity returns and Austrian bond returns. Immediately below this entry is the correlation between Austrian equity returns and Austrian bond returns.

Table 3c Unconditional correlations between bond returns.

	Belgium	Canada	Denmark	France	Germany	Ireland	Japan	The Netherlands	Sweden	Switzerland	United Kingdom	United States
Austria	0.914	0.070	0.884	0.896	0.950	0.809	0.441	0.947	0.647	0.844	0.626	0.186
Belgium		0.094	0.898	0.909	0.939	0.814	0.455	0.940	0.667	0.832	0.643	0.207
Canada			0.094	0.097	0.068	0.134	0.007	0.082	0.160	−0.019	0.167	0.452
Denmark				0.907	0.909	0.839	0.418	0.908	0.696	0.800	0.650	0.195
France					0.927	0.832	0.428	0.933	0.679	0.823	0.673	0.267
Germany						0.826	0.464	0.984	0.657	0.866	0.656	0.221
Ireland							0.359	0.835	0.664	0.710	0.699	0.212
Japan								0.458	0.294	0.475	0.343	0.038
The Netherlands									0.667	0.861	0.657	0.234
Sweden										0.553	0.566	0.173
Switzerland											0.589	0.126
United Kingdom												0.249

This table reports unconditional correlations of returns across the bond returns.

Table 4 Conditional partial covariances.

		Overall	Intrastock	Intrabond	Interstock bond
Significant at 10%		0.308	0.690	0.051	0.087
Significant at 20%		0.455	0.890	0.128	0.212
	Stocks only				
			Australasia	Europe	North America
	Australasia		0.800		
	Europe		0.677	0.807	
	North America		0.400	0.538	1.000
	Bonds only				
			Australasia	Europe	North America
	Australasia		–		
	Europe		0.000	0.889	
	North America		0.000	0.000	0.000
	Across stocks — bonds			Stocks	
			Australasia	Europe	North America
	Australasia		0.000	0.000	0.000
Bonds	Europe		0.020	0.146	0.033
	North America		0.333	0.000	0.100

This table reports summary statistics for conditional partial covariance. The top panel contains results for the test on the covariances, testing whether the covariance is higher after joint negative returns than after joint positive returns. The bottom three panels represent the percentage of the return cross-product series rejecting the null that the conditional partial covariance is the same after joint bad news (two negative returns) as after joint good news (two positive returns). A decomposition into three groups is considered: equity, bond, and cross equity–bond across the regions. Equities return series demonstrate stronger evidence of asymmetries than bond returns. Except where explicitly indicated, all tests were at the 10% level.

that the coefficients of the indicator variables are equal. All equity returns exhibit some significant increases to joint bad news, while six of the bond series do.

4 EMPIRICAL RESULTS

The first stage of the DCC model building consists of fitting univariate GARCH specifications to each of the 34 return series and selecting the *best* one according to the Bayesian information criterion. Table 5 contains the specifications of the GARCH processes selected and the estimated parameters. Eighteen of the 21 models selected for the equity returns include a significant asymmetric term. Asymmetry is introduced in the form of threshold effects in 16 specifications and by recentering the news impact curves in the remaining two where the AGARCH parameterization is adopted. As widespread as the evidence of asymmetric volatility is in the equity series, it is equally absent from the bond returns.

Table 5 Univariate GARCH models.

Asset	Model selected	ω^{a}	α	γ or δ	β
Australia stocks	ZARCH	0.0065	0.0808	0.0237	0.9074
Austria stocks	GARCH	0.0042	0.1197		0.8298
Belgium stocks	GJR-GARCH	0.0126	0.0703	0.2434	0.6184
Canada stocks	ZARCH	0.0114	0.0700	0.1373	0.8506
Denmark stocks	ZARCH	0.0170	0.0711	0.0875	0.8492
France stocks	GJR-GARCH	0.0105	0.0140	0.1800	0.7497
Germany stocks	ZARCH	0.0318	0.0503	0.1567	0.7905
Hong Kong stocks	EGARCH	−0.5931	0.4185	−0.1982	0.8560
Ireland stocks	EGARCH	−0.4799	0.2671	−0.1038	0.8870
Italy stocks	GARCH	0.0054	0.0646		0.8904
		0.0587	0.3926		0.0143
Japan stocks	EGARCH	−0.2097	0.1395	−0.0590	0.9559
Mexico stocks	GJR-GARCH	0.0223	0.0504	0.1801	0.7898
Netherlands stocks	EGARCH	−0.5684	−0.1541	0.3137	0.8887
New Zealand stocks	GARCH	0.0042	0.0839		0.8781
Norway stocks	AGARCH	0.0318	0.1451	0.1298	0.7845
Singapore stocks	ZARCH	0.0288	0.0815	0.2379	0.7886
Spain stocks	EGARCH	−0.3413	0.2388	−0.0777	0.9360
Sweden stocks	EGARCH	−0.3445	0.2246	−0.1425	0.9199
Switzerland stocks	ZARCH	0.0916	0.0000	0.2162	0.5731
U.S. stocks	ZARCH	0.0084	0.0369	0.0841	0.9098
U.K. stocks	ZARCH	0.0109	0.0564	0.1669	0.8474
Austria bonds	GARCH	0.0014	0.0723		0.8706
Belgium bonds	GARCH	0.0017	0.0723		0.8560
Canada bonds	ZARCH	0.0125	0.0048	0.0972	0.8477
Denmark bonds	AGARCH	0.0013	0.0416	0.0355	0.9584
France bonds	GARCH	0.0019	0.0872		0.8313
Germany bonds	GARCH	0.0017	0.0687		0.8608
Ireland bonds	GARCH	0.0005	0.0547		0.9271
Japan bonds	NGARCH	0.0112	0.1000	0.8894	0.6192
Netherlands bonds	GARCH	0.0018	0.0785		0.8453
Sweden bonds	GARCH	0.0004	0.0422		0.9423
Switzerland bonds	EGARCH	−0.4173	0.0825	0.0650	0.9007
U.K. bonds	GARCH	0.0001	0.0242		0.9706
U.S. bonds	GJR-GARCH	0.0008	0.0400	0.1475	0.7184

This table reports the selected specifications and parameter estimates for the univariate GARCH models used to standardize each return series. Italian stocks actually preferred a structural break in the model, with the first set of parameters referring to the data until the introduction of the euro, and the second subsequent.

[a]Intercept parameters are calculated on 10 times the returns to facilitate working with extremely small numbers.

Only three of the 13 models selected contain asymmetric terms, all of the threshold variety. This is consistent with the earlier evidence of little conditional difference in variances after negative shocks for bond returns (see Section 3).

Figure 1 plots the volatility news impact curves for five assets. The curves highlight the flexibility of DCC-family models. For instance, the model selected for Swedish equity returns is an EGARCH resulting in a news impact curve that is asymmetric with a much smaller increase in volatility after a positive than a negative shock. Likewise, the news impact curve for Canadian bond return volatility is near zero for all positive shocks and only increases for negative ones. Swiss bond returns, instead, show a surprising asymmetric response to *good* news with a larger increase in volatility subsequent to positive shocks.

Four different parameterizations are estimated for the dynamics of the correlation. The first and simplest model is a standard scalar DCC where no asymmetric terms are included [Equation (3)]. Second, a symmetric diagonal version is considered [i.e. in Equation (5) the matrices A and B are diagonal, while the matrix G is set equal to zero]. Next, two asymmetric specifications are estimated, an asymmetric scalar DCC model (where the matrices A, B, and G reduce to scalars) and the full diagonal version of this model [see Equation (5), with diagonal matrices A, B, and G]. Table 6a reports the results relative to these four

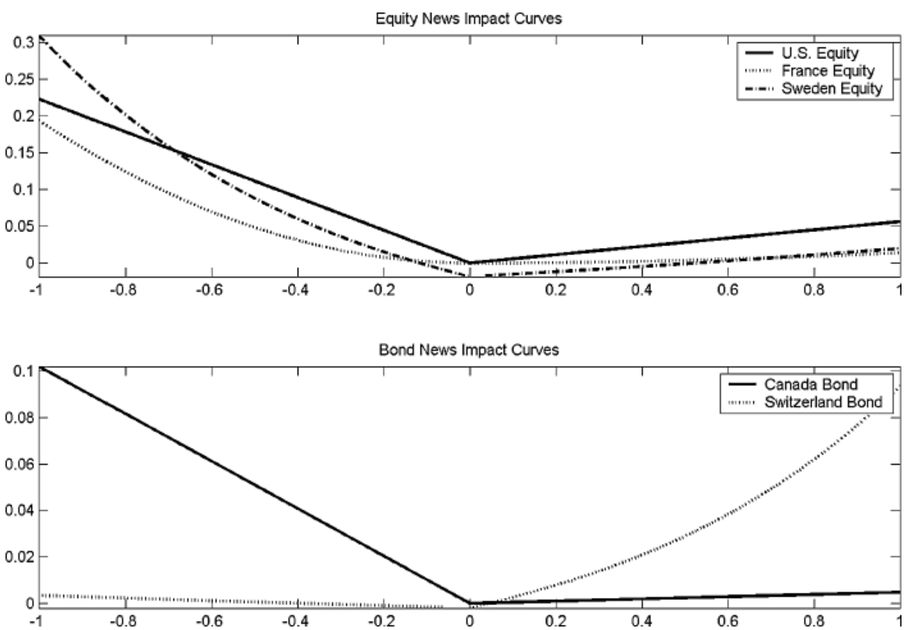

Figure 1 Typical volatility news impact curves for equities and bonds. The volatility dynamics can take on a wide range of forms, including decreasing for positive shocks in the case of an EGARCH model (Swedish equities), or showing no increase subsequent to a positive shock in the case of Canadian bond returns.

Table 6a DCC GARCH models.

	Symmetric model		Asymmetric model		
	a_i^2	b_i^2	a_i^2	g_i^2	b_i^2
Australia stocks	0.0002*	0.9641	0.0062	0.0078	0.7899
Austria stocks	0.0084	0.9481	0.0032	0.0042	0.9606
Belgium stocks	0.0139	0.9490	0.0104	0.0081	0.9501
Canada stocks	0.0066	0.9186	0.0051	0.0024	0.9523
Denmark stocks	0.0077	0.9468	0.0034	0.0052	0.9646
France stocks	0.0094	0.9438	0.0086	0.0027	0.9454
Germany stocks	0.0122	0.9448	0.0071	0.0066	0.9568
Hong Kong stocks	0.0022	0.9655	0.0004*	0.0022	0.9563
Ireland stocks	0.0045	0.9647	0.0002*	0.0067	0.9677
Italy stocks	0.0135	0.9488	0.0071	0.0117	0.9569
Japan stocks	0.0026	0.9497	0.0020	0.0026	0.9526
Mexico stocks	0.0012	0.9635	0.0009*	0.0189	0.9375
Netherlands stocks	0.0099	0.9562	0.0061	0.0091	0.9587
New Zealand stocks	0.0000*	0.9574*	0.0010*	0.0009*	0.9215
Norway stocks	0.0076	0.9235	0.0017	0.0057	0.9290
Singapore stocks	0.0013	0.9492	0.0006*	0.0021	0.9760
Spain stocks	0.0090	0.9463	0.0055	0.0073	0.9538
Sweden stocks	0.0075	0.9676	0.0049	0.0055	0.9649
Switzerland stocks	0.0118	0.9542	0.0145	0.0092	0.9427
U.K. stocks	0.0079	0.9484	0.0066	0.0064	0.9549
U.S. stocks	0.0090	0.9261	0.0020	0.0040	0.9512
Austria bonds	0.0131	0.9759	0.0096	0.0087	0.9762
Belgium bonds	0.0168	0.9712	0.0112	0.0089	0.9745
Canada bonds	0.0077	0.9418	0.0053	0.0056	0.8593
Denmark bonds	0.0186	0.9678	0.0111	0.0090	0.9731
France bonds	0.0146	0.9721	0.0106	0.0079	0.9734
Germany bonds	0.0167	0.9712	0.0131	0.0090	0.9715
Ireland bonds	0.0161	0.9700	0.0138	0.0065	0.9675
Japan bonds	0.0087	0.9627	0.0047	0.0063	0.9642
Netherlands bonds	0.0166	0.9714	0.0132	0.0076	0.9716
Sweden bonds	0.0119	0.9618	0.0081	0.0117	0.9615
Switzerland bonds	0.0138	0.9754	0.0117	0.0067	0.9740
U.K. bonds	0.0091	0.9689	0.0058	0.0041	0.9716
U.S. bonds	0.0096	0.9277	0.0058	0.0027	0.9361
Scalar model	0.0101	0.9425	0.0081	0.0065	0.9481

This table reports parameter estimates for the symmetric and asymmetric DCC GARCH models.
*Insignificance at the 5% level.

DCC specifications. Most parameters are significantly different from zero, with exceptions noted in the table. The shocks to correlation are typically highly persistent, with a half-life of more than 14 weeks for the symmetric scalar DCC model. For the diagonal symmetric DCC model, the half-life of the innovation ranges from nine to over 63 weeks.[9]

Upon inspection of the fit correlation and the data, it becomes obvious that a large number of the series have undergone a significant structural break when, within the European Monetary Union (EMU),[10] exchange rates were irrevocably fixed.[11] To take this into account, all the four base models are modified to allow for a structural break in the intercept and for structural breaks in both the intercept and the dynamics of the correlation process. The log-likelihoods of the resulting 12 specifications (each of the four DCC models is estimated without any break, with a break in the intercept, and with breaks in the intercept and in the dynamics) are reported in Table 6b. For all models, we overwhelmingly reject the null of no structural break in the mean; yet the evidence for both a break in the mean and the dynamics is less compelling. In addition, allowing for a break reduces the persistence of the series to approximately 10 weeks[12] and can be interpreted as further evidence in support of the break. Structural breaks in the intercept parameter of GARCH models have been studied in Hillebrand (2005). In this simplification, breaks cause spurious persistence but do not generate spurious asymmetries. The dynamics of a DCC model would behave in a similar manner.

Log-likelihood values also suggest that the diagonal versions significantly outperform the scalar specifications. Moreover, both the asymmetric DCC models outperform their non-A-DCC counterparts with p-values near zero.

When the model allowing for both breaks in the mean and in the dynamics was estimated, despite the higher log-likelihood, many parameters were insignificant after the break. This may be due to either stable parameters or the relatively short sample available after the introduction of the fixed exchange regime. To avoid these poorly estimated parameters, the model with only breaks in the mean but not in the dynamics was chosen. Therefore, the remainder of the article presents results from the diagonal AG-DCC model with a break in the intercept but not in the dynamics.

Figures 2*a*, 2*b* and 3 plot news impact *surfaces* for German–U.S. equity correlation and covariance, respectively. The correlation news impact surface is highly

[9] The half-life is defined as the time at which a shock to correlation is expected to be halfway dissipated. Making the approximation recommended in Engle and Sheppard (2001) that $Q_t = P_t$, the half-life is computed as $\ln(0.5)/\ln(a^2 + b^2)$. In the asymmetric DCC, a similar formula does not apply because the expectation of the cross product of the returns is not available.

[10] The countries which in 2002 were part of the EMU are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain.

[11] Although it would be ideal to test each series for a break at all points in time, this procedure is infeasible as the parameters of the model are not identified under the null of no break, making standard testing theory incorrect. We choose to include the break on January 1999, when the euro was introduced, as we expect that equity and bond correlations increase among EMU member states and possibly among other countries as well towards the end of the sample.

[12] Persistence is measured as the half-life of a shock, computed as $\ln(0.5)/\ln(a^2 + b^2)$.

Table 6b Log-likelihood values.

Model	Log-likelihood value	Number of parameters in the correlation evolution	Approximate BIC
DCC	−25722.1	561 + 2	−1.057
DCC w/ mean break	−24816.2	1122 + 2	−0.743
DCC w/ mean and dynamics breaks	−24789.2	1122 + 4	−0.742
G-DCC	−25564.5	561 + 68	−0.853
G-DCC w/ mean break	−24572.5	1122 + 68	−0.723
G-DCC w/ mean and dynamics breaks	−24483.3	1122 + 136	−0.708
A-DCC	−25704.7	561 + 3	−0.869
A-DCC w/ mean break	−24809.2	1122 + 3	−0.742
A-DCC w/ mean and dynamics breaks	−24781.6	1122 + 6	−0.741
AG-DCC	−25485.1	561 + 102	−0.844
AG-DCC w/ mean break	−24487.5	1122 + 102	−0.714
AG-DCC w/ mean and dynamics breaks	−24398.3	1122 + 204	−0.694

A-DCC, Asymmetric Dynamic Conditional Correlation; AG-DCC, Asymmetric Generalized Dynamic Conditional Correlation; BIC, Bayesian Information criterion; G-DCC, Generalized Dynamic Conditional Correlation.

This table reports log-likelihood values for 12 estimated DCC GARCH models. There is a significant increase in the log likelihood when either asymmetric effects or breaks in the mean are introduced. Allowing for breaks in the dynamics is not significant in the diagonal models although it does reduce the BIC.

asymmetric, showing a larger response to shocks in the −/− than in the +/+ quadrant (i.e., it is more responsive to joint bad news than to joint good news of the same magnitude). When we analyze the covariance news impact surface, the asymmetry becomes even more striking, with a huge increase for joint negative shocks, little change for larger positive shocks, and asymmetries in all four quadrants.

4.1 Volatility Dynamics and Linkages

Although each of the volatility models is parameterized to evolve independently of the others, we examine volatility linkages across countries. A simple criterion to analyze these linkages is the correlation between the estimated variances of two assets:

$$\rho_{h_{it}h_{jt}} = \frac{\sum_{t=1}^{T}\left(h_{it}-\bar{h}_i\right)\left(h_{jt}-\bar{h}_j\right)}{\sqrt{\sum_{t=1}^{T}\left(h_{it}-\bar{h}_i\right)^2 \sum_{t=1}^{T}\left(h_{jt}-\bar{h}_j\right)^2}}. \tag{11}$$

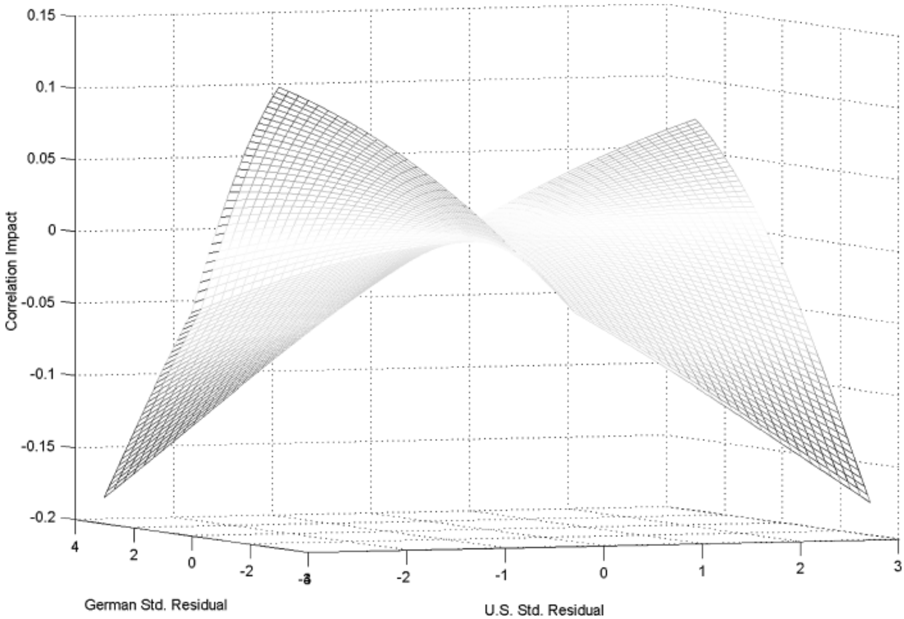

Figure 2a Correlation news impact surface for German and U.S. equity returns. There is significant asymmetry in the negative–negative quadrant.

The conditional variances of the equity markets are moderately correlated at the global level, with an average correlation of 0.325, and are similar both before and after the introduction of the fixed exchange rate regime system in Europe. However, the volatility linkages are much stronger at the regional level. For instance, the correlation of the volatility of European equity markets is 0.546 over the entire sample and is similar before and after the introduction of the euro. The American equity markets' variances are also highly correlated, averaging 0.612, while the correlation between U.S. and Canadian equity volatilities was extremely high at 0.796. Australasian equity volatility correlation is similar to the overall average at 0.418, although this is in part due to low correlation between the variances of New Zealand with the rest of this group. Not surprisingly, the correlation among the variances of mature markets is higher than that of emerging markets.[13]

Figure 4 contains a plot of the annualized average volatility series for four groups of equities: European excluding the EMU countries, EMU, American, and Australasian. The volatility linkages were most evident during certain tumultuous periods: black Tuesday in October 1987, the Iraqi invasion of Kuwait, and the

[13] For instance, the correlation of volatility between France, Germany, and the United States, vis-à-vis the U.K. equity markets averages 0.706.

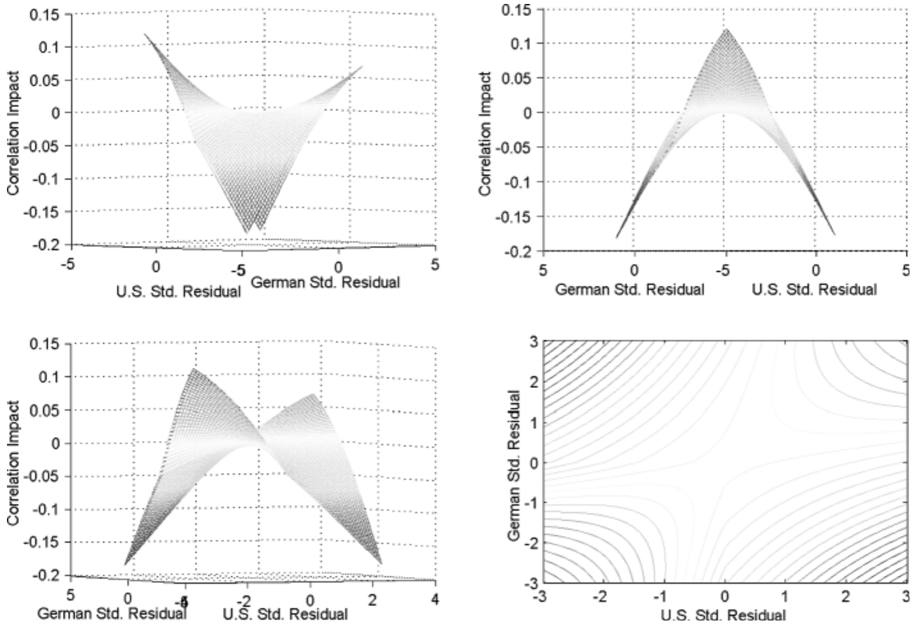

Figure 2b Four looks at the correlation news impact surface for German and U.S. equity returns. The asymmetry is apparent in the upper left and the lower right contour plot. There is little asymmetry between +− and −+ standardized returns.

Gulf war in 1990/1991, during the financial crises which gripped Russia, Southeast Asia, and Latin America in 1997/1998, when signs of a slowdown in the world economy started to affect equity markets in March 2001, and when terrorist attacks hit the United States in September 2001. Interestingly, volatility increased for European Union countries in 1992 and 1993 when there was tension within the European Monetary System which resulted in interest rate increases and exchange rate realignments.

Similarly, bond volatility demonstrates low correlation when considered on a global scale, although regional linkages are strong. The overall average correlation between bond return variances is 0.352, whereas correlation between European bond variances is 0.530 and, among EMU member countries, 0.795.

Figure 5 represents plots of the annualized average bond return volatility in the EMU countries, the United States, and Japan. Bond returns were much less volatile than the equity markets and demonstrate weaker linkages across regions. Turbulences in equity markets are sometimes reflected in bond volatilities, pointing towards a "flight to quality phenomenon," with investors moving capital from equities to bonds.

To ensure that structural changes in conditional correlations are not due to breaks in volatilities, we also test for structural breaks in the level and both in the

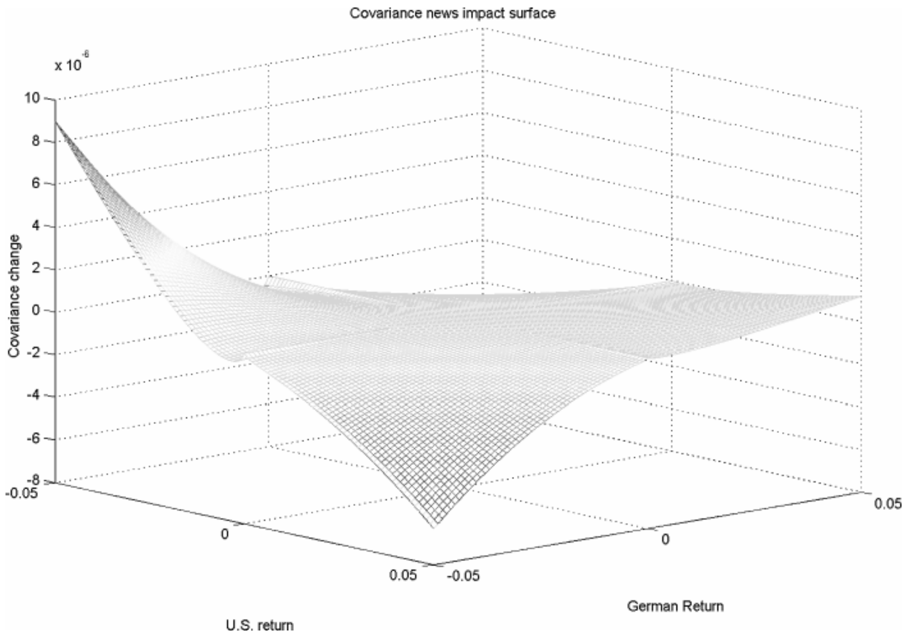

Figure 3 News impact surface for covariance. Although the news impact surface is increasing in both the ++ and the −− quadrants, the correlation combined with the two variances results in a steep increase in the −− quadrant and a near flat response in the ++ quadrant, as well as asymmetries between the +− and the −+ quadrants.

level and the dynamics of volatility models.[14] Likelihood ratio tests reject the null of no structural breaks in only six of the 34 series.[15]

4.2 Correlation Dynamics

The correlations of the assets under consideration show considerable variation. Figure 6 plots the estimated equity correlation between three countries within the EMU (France, Germany, and Italy) and Great Britain. The correlation has clearly increased between these four countries since the introduction of the euro (indicated by the dashed vertical line). The adoption of a common monetary policy and the consequent irrevocable fixing of exchange rates have led to much higher correlations between equity returns not only in the three EMU countries but also in the United Kingdom. The increase between France, Germany, and Italy has,

[14] We assume the specification of the model dynamics remain constant when testing for structural breaks in the parameters.

[15] Using the Bayesian information criterion, a model with breaks of either type was only preferred for Italian equity returns.

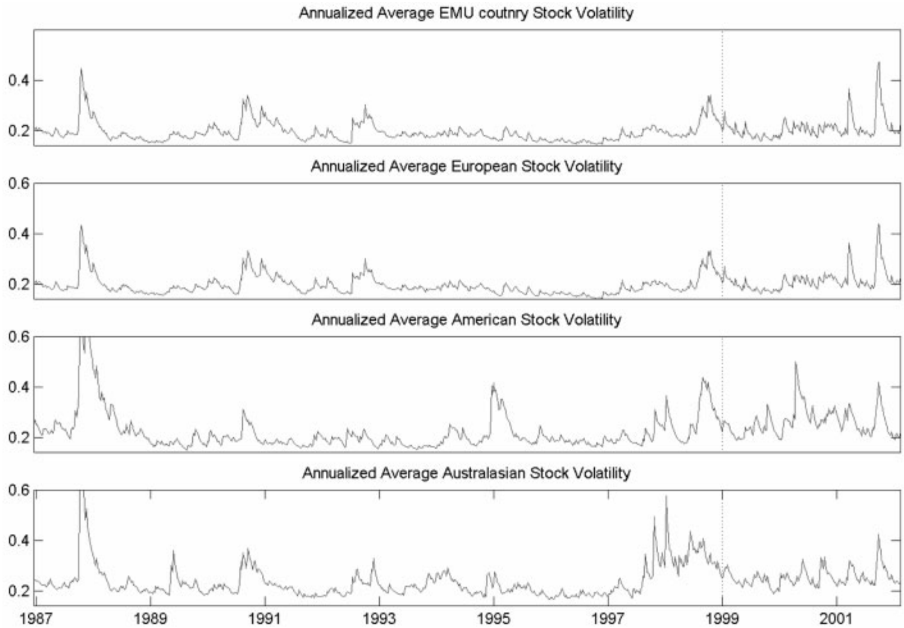

Figure 4 Plots of the annualized conditional equity volatility for four groups of countries. There appear to be strong linkages in equity volatility across regions, evidenced by the crash of October 1987, the Gulf war in mid-1990–1991, the Asian financial crisis of 1997–1998, and the terrorist attacks of late 2001.

however, been more pronounced, as evidenced by a rise from an average of 0.620 to 0.852 for France–Germany, 0.462 to 0.825 for France–Italy, and from 0.447 to 0.812 for Germany–Italy. The correlation between Great Britain and the three EMU countries has also increased, although to a lesser extent, with an average correlation between the United Kingdom and the three EMU countries rising from 0.463 to 0.680.

Figure 7 represents the average equity correlations for the EMU countries, Europe excluding the EMU member states, the Americas, and Australasia. October 1987 stands out across the four groups with ubiquitous spikes in the correlation in all six series. While there appear to be increases in the correlations between the EMU, Europe without the EMU, and the Americas, the correlations between these three regions and the Australasian group seem to be unaffected.

There are many explanations for these rising correlations beyond the launch of the euro. The general increases seen especially between Europe and the Americas may be due to globalization, sectoral rotation, asymmetry in markets, or rising volatilities. Globalization gives rise to multinational companies, whose asset prices will reflect economic shocks in many countries and sectors. Consequently, equity returns will be highly correlated across countries. With the major run-up of technology stocks in the late 1990s, many value-weighted indices became heavily

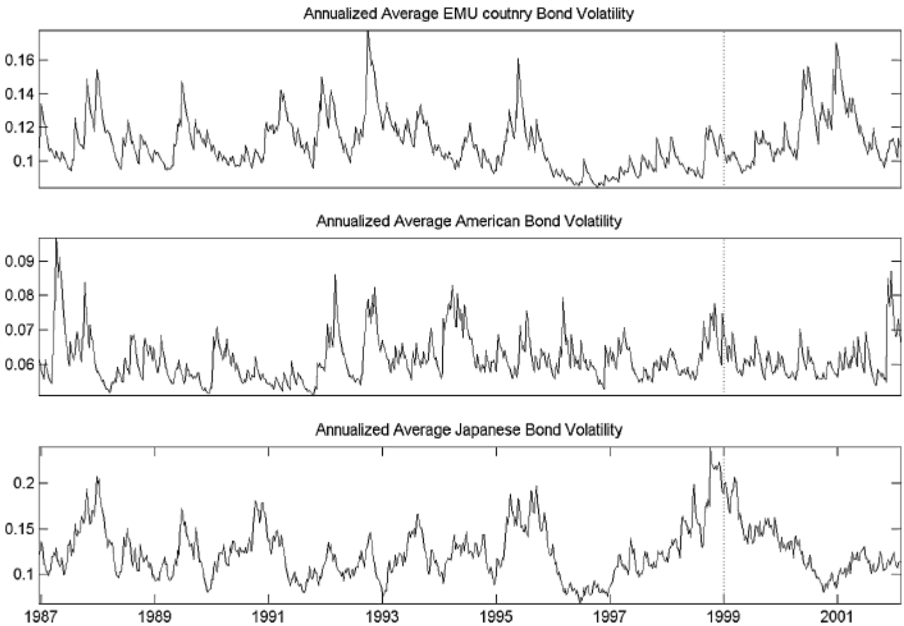

Figure 5 Plots of the annualized conditional bond return volatility for the EMU countries, the United States, and Japan. Unlike equities, bond markets do not exhibit strong linkages in volatility.

weighted with technology companies. This, in turn, let correlation among these equity indices go up. When the bubble burst, technology companies all over the world witnessed large decreases in value, which, again, may have led to a general increase in correlation. Although appealing, the investigation of this idea is beyond the scope of this article. However, because our model does show that correlations tend to rise as markets decline, some of this effect is already incorporated. Furthermore, in simple factor structures, rising volatility of broad indices will lead to increased correlation of the assets depending on it as long as idiosyncratic volatilities do not increase correspondingly. This argument leads to an expectation of comovement between correlations and volatilities that will be explored below.

Bond and equity market correlations appear to be, on the one hand, similar in that there have been some radical changes since the introduction of the fixed exchange rate regime and, on the other hand, dissimilar in that linkages across regions seems to be much weaker. Figure 8 represents the average bond return correlations between the EMU, the remainder of Europe, and the Americas. Both the average correlation between EMU and European markets not belonging to the EMU and correlation between American and EMU markets appear to have increased after the fixed exchange regime went into effect. Finally, the average

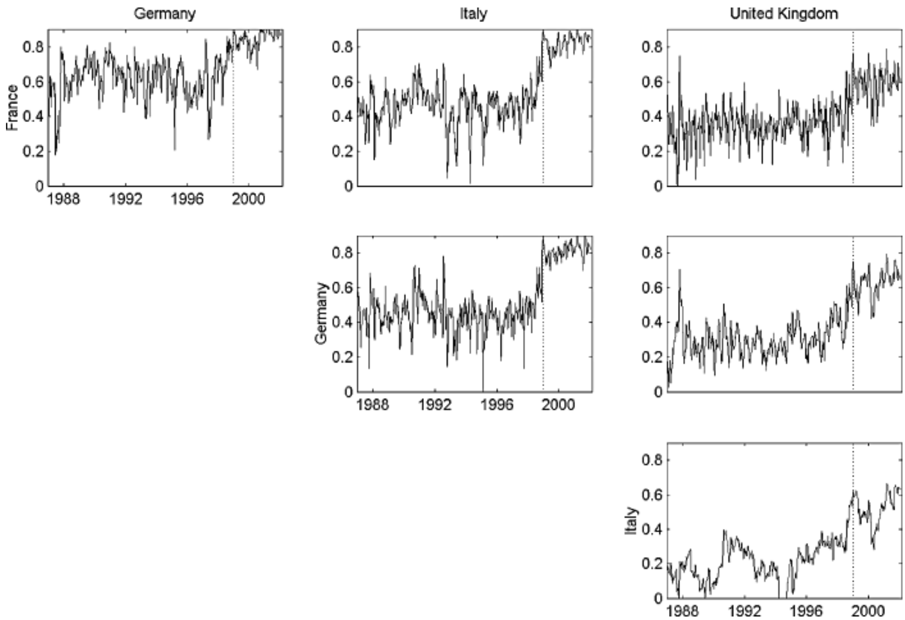

Figure 6 Plots of the conditional correlation of equity returns for four European countries, three of which are in the EMU. There is a strong increase in correlation on January 1, 1999 for all four countries, and the increase was larger within the EMU countries than between Great Britain and the three EMU countries.

correlation between European non-EMU member countries and the Americas also seems to have increased. It is important to note that although the correlation between the American and both the European groups' bond returns has increased towards the end of the 1990s and into the new millennium, the levels are still very different. The correlation between bond returns in Europe is typically 0.743, although the correlation between either of the European groups and the Americas is less than half, averaging near 0.336. This is unsurprising given the many common economic factors that affect European countries both within and outside the EMU.

Figure 9 represents correlations between three of the largest providers of government bonds: Germany, Japan, and the United States. The correlation between German and Japanese bond returns plummeted with the introduction of the fixed exchange rate regime, from a value around 0.528 to an average near zero. At the same time, German and U.S. bond returns have become increasingly correlated, whereas U.S. and Japanese bond correlation has remained, for the entire sample, in a fairly narrow range averaging close to zero.

Figure 10 illustrates plots of the average correlation between the various equity markets and the EMU bond returns. Not surprisingly, EMU bond and equity returns are relatively highly correlated, although correlation between EMU bond returns, on the one hand, and American and Australasian equity returns, on

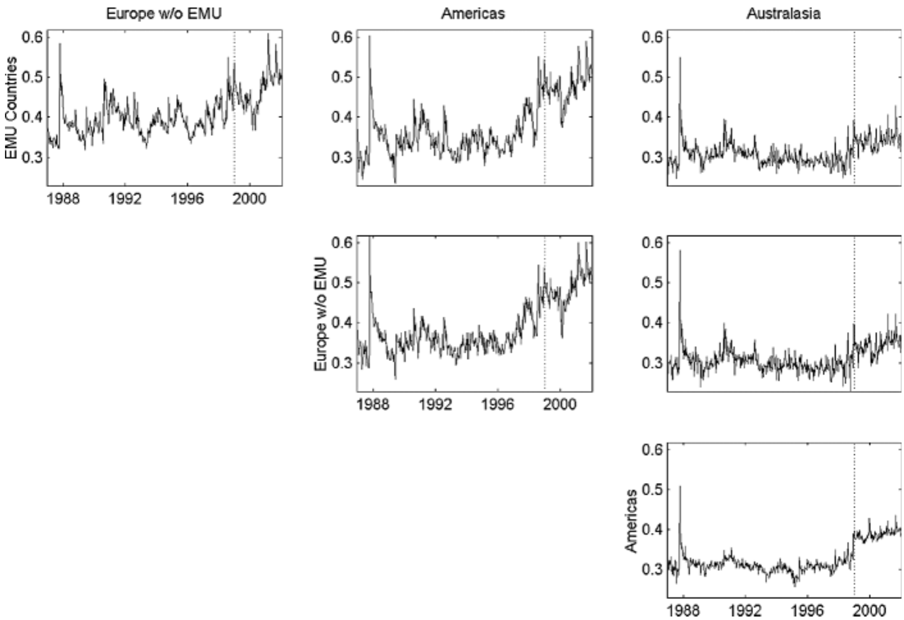

Figure 7 Plots of the average correlation of equity returns between equity in the EMU countries, the remainder of Europe, the Americas, and Australasia. With the exception of 1987, simultaneous increases in correlation appear to be more widespread than decreases.

the other hand, is typically near zero and often negative. All three pictures show a decline in correlation around October 1987, providing evidence to a flight to quality. The levels notwithstanding, the dynamics of the three series are remarkably similar.

4.3 Joint Volatility and Correlation Dynamics

The relationships between volatilities and correlations are important for many financial decisions, including risk management and pricing derivatives. If correlations and volatilities move together, then risks in the long run are greater than they seem in the short run. Insurance in the form of options or credit derivatives will also be more expensive than one would otherwise expect.

We can examine whether, on average, volatilities and correlations are positively or negatively related. We define the average correlation of one asset's variance with all its associated pairwise correlations as follows:

$$\phi_i = \frac{1}{k-1} \sum_{j=1, j \neq i}^{k} \frac{\sum_{t=1}^{T} \left(h_{it} - \bar{h}_i\right)\left(\rho_{ijt} - \bar{\rho}_{ij}\right)}{\sqrt{\sum_{t=1}^{T} \left(h_{it} - \bar{h}_i\right)^2 \sum_{t=1}^{T} \left(\rho_{ijt} - \bar{\rho}_{ij}\right)^2}}. \tag{12}$$

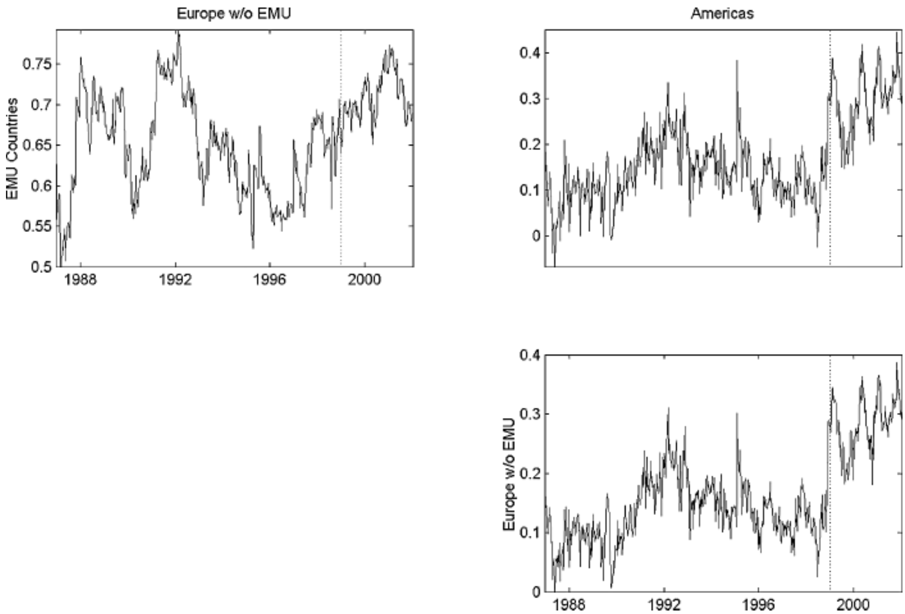

Figure 8 Plots of bond return correlation between the EMU, the rest of Europe, and the United States. The introduction of the euro seems to have increased correlation between the EMU countries and the United States, whereas correlations between the EMU and the non-EMU European countries appear to be similar to before the introduction of the euro.

For example, for Australian equities, ϕ_i is the correlation between the Australian equity variance and the correlations between Australian and Austrian equities, Australian and Belgian equities, etc. In this case, $\phi_i = 0.510$, indicating that as Australian volatilities rise, all its pairwise equity correlations increase as well. When ϕ_i is computed over all equity correlations, including those not involving Australia, its value declines to 0.288. Tables 7 and 8 report the values of ϕ_i relative to each equity and bond series, respectively. The indicator turns out to be mostly positive, suggesting that volatilities and correlations move together. This phenomenon appears to be stronger for equities than bonds.

5 CONCLUSIONS

This article generalizes the DCC GARCH model of Engle (2002) along two dimensions: we allow for series-specific news impact and smoothing parameters and permit conditional asymmetries in correlation dynamics. The resulting AG-DCC GARCH model is flexible and yet empirically tractable. We use the AG-DCC specification to investigate asymmetries in conditional variances and correlation dynamics for a broad cross-section of national equity and government bond returns. While conditional volatilities of equity returns show widespread

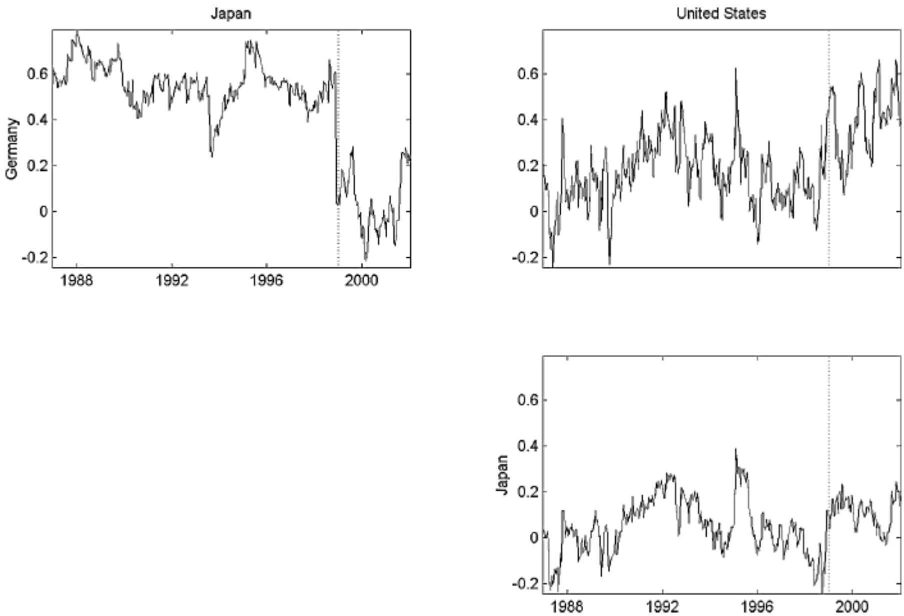

Figure 9 Bond return correlation between three leading providers of government bonds, Germany, Japan, and the United States. The correlation between Japanese bond returns and German bond returns dropped dramatically at the introduction of the euro, whereas correlation between German and U.S. bond returns has increased although with increasing noise.

evidence of asymmetry, little is found for bond returns. However, both equities *and* bonds exhibit asymmetry in conditional correlation, although equities show a stronger response than bonds to joint bad news. Finally, we explore the dynamics and changes in the correlation of the asset markets under consideration. When compared with scalar and/or symmetric representations, the AG-DCC GARCH model turns out to be superior.

We document strong comovements in equity market volatility. Annualized average volatility series for European countries excluding those in the EMU, EMU, American, and Australasian equities show linkages during periods of financial turmoil, such as the stock market crash in 1987, the beginning of the Gulf war, and the Asian financial crisis. Unlike equity returns, bond market volatilities demonstrate less clear linkages, exhibiting, instead, increases to region-specific events.

Upon the creation of the irrevocably fixed exchange rate regime in Europe, significant evidence of a structural break is found in the level of conditional correlation but not in the levels of the conditional volatilities. Conditional equity correlations for the major markets of Europe, that is, France, Germany, and Italy (which are part of the EMU) and United Kingdom (which is not part of the EMU), have increased since the introduction of the single currency. We also find evidence of a meaningful increase in correlation of other markets with the EMU

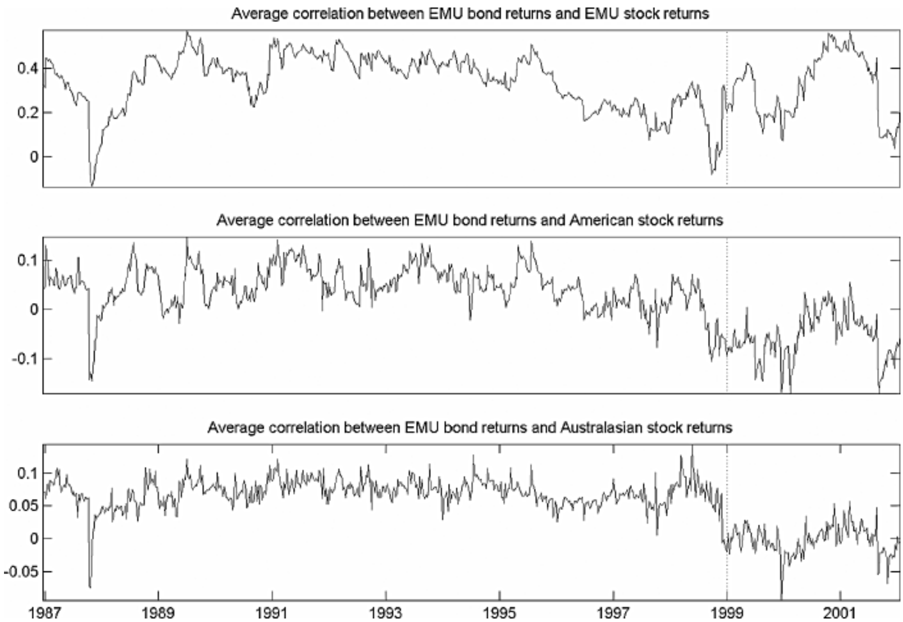

Figure 10 Plots of the average correlations between EMU bond returns and equity returns from the three main regions. There appear to be very strong linkages in the three series, as evidenced by October 1987, 1997–1998, and late 2001.

countries, possibly signaling stronger economic ties. Furthermore, the introduction of a fixed exchange rate regime has led to near perfect correlation among bond returns within EMU member states. This is not surprising and mainly driven by the monetary policy harmonization.

When bad news hits financial markets, conditional equity correlation series among regional groups increases dramatically. This finding has important implications for international investors, as the diversification sought by investing in multiple markets is likely to be lowest when it is most desirable. However, it is also evidenced that conditional correlation between equity and bond returns typically declines when stock markets suffer from financial turmoil, an indication of a "flight to quality" phenomenon, where investors move capital from equities to safer assets.

The developments of the volatility and correlation dynamics documented in this paper raise significant issues for academics and practitioners alike. For instance, can the risk of increasing correlation occurring during down markets be hedged? Why do both equities and bonds demonstrate asymmetric changes in correlation when they both decline? Has the introduction of the euro fundamentally changed world equity markets and how will this affect expected returns, capital flows, and exchange rates both within and outside the euro area?

Table 7 Average correlation between equity variance and all its pairwise equity correlations and with all equity correlations.

Australia stocks	0.5103	0.2879
Austria stocks	0.3547	0.1704
Belgium stocks	0.1972	0.2805
Canada stocks	0.3150	0.2748
Denmark stocks	0.2492	0.2253
France stocks	0.2509	0.3464
Germany stocks	0.3979	0.3691
Hong Kong stocks	0.1474	0.1575
Ireland stocks	0.3871	0.3198
Italy stocks	0.1393	0.1820
Japan stocks	0.2165	0.2233
Mexico stocks	0.0647	0.2051
Netherlands stocks	0.3256	0.3476
New Zealand stocks	0.5076	0.3486
Norway stocks	0.3473	0.3538
Singapore stocks	0.3229	0.2868
Spain stocks	0.3189	0.3698
Sweden stocks	0.4179	0.3611
Switzerland stocks	0.2841	0.2437
U.K. stocks	0.3840	0.3514
U.S. stocks	0.3297	0.3426
Overall Stocks	0.3080	0.2880

The left column of this table contains the average correlation between the conditional variance of the equity series listed on the left with the correlation between this market and the other equity markets. The right column contains the average correlation between the conditional variance of the equity series listed on the left with the correlation between this market and all other markets, equity, and bond.

APPENDIX: UNIVARIATE VOLATILITY MODELS AND NEWS IMPACT SURFACES

A.1 Univariate GARCH Models

In this appendix, we describe the univariate GARCH specifications which we use in this study. Although some of the models below differ from their original representations, their qualitative features remain unchanged. The models are modified to improve their comparability.
GARCH:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}.$$

Absolute value GARCH (AVGARCH):

$$h_t^{1/2} = \omega + \alpha|\varepsilon_{t-1}| + \beta h_{t-1}^{1/2}.$$

Table 8 Average correlation between bond volatility and all its pairwise bond correlations and with all bond correlations.

Austria bonds	0.3278	0.2660
Belgium bonds	0.1778	0.2556
Canada bonds	−0.1176	−0.0533
Denmark bonds	0.1850	0.2340
France bonds	0.2669	0.2632
Germany bonds	0.2802	0.2585
Ireland bonds	0.2371	0.1687
Japan bonds	0.0948	−0.0074
Netherlands bonds	0.2735	0.2536
Sweden bonds	−0.0238	0.0612
Switzerland bonds	0.1218	0.1084
U.K. bonds	0.3106	0.0739
U.S. bonds	0.1243	−0.0091
Overall bonds	0.1737	0.1441

The left column of this table contains the average correlation between the conditional variance of the bond series listed on the left with the correlation between this market and the other bond markets. The right column contains the average correlation between the conditional variance of the bond series listed on the left with the correlation between this market and all other markets, equity, and bond.

Nonlinear GARCH (NARCH):

$$h_t^{\lambda/2} = \omega + \alpha|\varepsilon_{t-1}|^{\lambda} + \beta h_{t-1}^{\lambda/2}.$$

Exponential GARCH (EGARCH):

$$ln(h_t) = \omega + \alpha\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \gamma\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta\, ln(h_{t-1}).$$

Threshold GARCH (ZARCH):

$$h_t^{1/2} = \omega + \alpha|\varepsilon_{t-1}| + \gamma I[\varepsilon_{t-1} < 0]|\varepsilon_{t-1}| + \beta h_{t-1}^{1/2}.$$

Glosten–Jagannathan–Runkle GARCH (GJR-GARCH):

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I[\varepsilon_{t-1} < 0]\varepsilon_{t-1}^2 + \beta h_{t-1}.$$

Asymmetric power GARCH (APARCH):

$$h_t^{\lambda/2} = \omega + \alpha|\varepsilon_{t-1}|^{\lambda} + \gamma I[\varepsilon_{t-1} < 0]|\varepsilon_{t-1}|^{\lambda} + \beta h_{t-1}^{\lambda/2}.$$

Asymmetric GARCH (AGARCH):

$$h_t = \omega + \alpha(\varepsilon_{t-1} + \gamma)^2 + \beta h_{t-1}.$$

Nonlinear asymmetric GARCH (NAGARCH):

$$h_t = \omega + \alpha\left(\varepsilon_{t-1} + \gamma\sqrt{h_{t-1}}\right)^2 + \beta h_{t-1}.$$

The simplest of the models are GARCH, AVGARCH (a GARCH on standard deviations instead of variances), and NARCH, followed by GJR-GARCH, ZARCH, and EGARCH (which all allow for threshold effects but use different powers of the variance in the evolution equation), and APARCH (which encompass both threshold effects and an estimated power for the evolution of variance). AGARCH and NAGARCH differ in that asymmetries in the news impact curve are modeled by a recentering of the curve, instead of a slope change which depends on the sign of past innovations. For the models which include a leverage term, the conditional variance will exhibit leverage whenever $\gamma > 0$.

A.2 Correlation News Impact Surfaces

In this section, we describe the correlation news impact surfaces which we use in the article.

$$f(e_i, e_j) = \frac{\tilde{c}_{ij} + (a_i a_j + g_i g_j) e_i e_j + b_i b_j \rho_{ij,t}}{\sqrt{\left[\tilde{c}_{ii} + (a_i^2 + g_i^2) e_i^2 + b_i^2\right]\left[\tilde{c}_{jj} + \left(a_j^2 + g_j^2\right) e_j^2 + b_j^2\right]}}, \quad \textit{for } e_i, e_j < 0,$$

$$f(e_i, e_j) = \frac{\tilde{c}_{ij} + a_i a_j e_i e_j + b_i b_j \rho_{ij,t}}{\sqrt{\left(\tilde{c}_{ii} + a_i^2 e_i^2 + b_i^2\right)\left[\tilde{c}_{jj} + \left(a_j^2 + g_j^2\right) e_j^2 + b_j^2\right]}}, \quad \textit{for } e_i > 0, e_j < 0,$$

$$f(e_i, e_j) = \frac{\tilde{c}_{ij} + a_i a_j e_i e_j + b_i b_j \rho_{ij,t}}{\sqrt{\left(\tilde{c}_{ii} + a_i^2 e_i^2 + b_i^2\right)\left[\tilde{c}_{jj} + \left(a_j^2 + g_j^2\right) e_j^2 + b_j^2\right]}}, \quad \textit{for } e_i > 0, e_j < 0,$$

$$f(e_i, e_j) = \frac{\tilde{c}_{ij} + a_i a_j e_i e_j + b_i b_j \rho_{ij,t}}{\sqrt{\left(\tilde{c}_{ii} + a_i^2 e_i^2 + b_i^2\right)\left(\tilde{c}_{ij} + a_i^2 e_i^2 + b_i^2\right)}}, \quad \textit{for } e_i, e_j > 0.$$

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