Asymmetric Dynamics in the Correlations Of

Global Equity and Bond Returns

Lorenzo Cappiello§
European Central Bank

Robert F. Engle†
NYU Stern School of Business and
University of California at San Diego

Kevin Sheppard‡
University of California at San Diego

Abstract

This paper investigates asymmetries in conditional variances, covariances, and correlations in international equity and bond returns. The analysis is carried out through an asymmetric version of the Dynamic Conditional Correlation (DCC) model of Engle (2002), which is particularly well suited to examine correlation dynamics among assets. Particular attention is given to whether changes in the correlation of international asset markets demonstrate evidence of asymmetric response to negative returns. Widespread evidence is found that national equity index return series show strong asymmetries in conditional volatility, yet little evidence is seen that bond index returns exhibit this behavior. However, both bonds and equities exhibit asymmetry in conditional correlation, although in systematically different manners. The paper also examines the strong worldwide linkages in the dynamics of volatility and correlation, finding subtle but important differences between equity and bond second moment dynamics. It is also found that beginning in January 1999 with the introduction of the Euro, there is significant evidence of a structural break in correlation, although *not* in volatility. The introduction of a fixed exchange rate regime leads to near perfect correlation among bond returns within EMU countries, which is not surprising in consideration of the monetary policy harmonization within the EMU. However, the increase in return correlation is not restricted to EMU countries and equity return correlation both within and outside the EMU also increases after January 1999.

JEL Codes: F3, G1, C5
Keywords: International Finance, Correlation, Variance Targeting, Multivariate GARCH, International Stock and Bond correlation

---

§Email. lorenzo.cappiello@ecb.int
†Email: robert.engle@stern.nyu.edu
‡ Email: ksheppar@econ.ucsd.edu. Software used in the estimation of this paper can be found at http://weber.ucsd.edu/~ksheppar in the research section. Kevin Sheppard would like to acknowledge financial support from the European Central Bank. While all efforts have been made to ensure that there are no errors in the paper, remaining errors are the sole responsibility of the authors.

I. Introduction

Typically, portfolio diversification is achieved using two main strategies: investing in different classes of assets thought to have little or negative correlation or investing in similar classes of assets in multiple markets through international diversification. While these two strategies have both solid theoretical justification and strong empirical evidence exists as to the benefits, investors must be aware that correlation is dynamic and varies over time, changing the amount of portfolio diversification within a given asset allocation. In particular, a number of studies document that correlation between equity returns increases during bear markets and decreases when stock exchanges rally (see, among others, Erb, Harvey and Viskanta, (1994), De Santis and Gerard, (1998), Ang and Bekaert, (2001), Das and Uppal, (2001), and Longin and Solnik, (2001)).

Over the past 20 years, a tremendous literature has developed where the dynamics of the covariance of assets has been explored, although the primarily focus has been on univariate volatilities and not correlations (or covariances). Among other regularities, (conditional) estimates of the second moments of equities often exhibit the so-called "asymmetric volatility" phenomenon, where volatility increases more after a negative shock than after a positive shock of the same magnitude; in fact, evidence has been proffered that volatility may fail to increase or even fall subsequent to a positive shock for certain assets.[1] Asymmetric effects have also been recently found in conditional correlations, although the economic reasoning behind these effects has not been widely researched.[2]

The need to take into account the asymmetric effects on conditional second moments has an appealing economic justification. Assume, for instance, that a negative return shock generates more volatility than a positive return innovation of the same magnitude. When, as commonly done, a traditional *symmetric* Generalized Autoregressive Conditionally Heteroskedasticity (GARCH) process is used to model second moments, the estimated conditional volatility which occurs after a price drop will be too small; similarly, the estimated conditional volatility which follows a price increase will be too large. Consequences such as asset mispricing and poor in- and out-of-sample forecasts will be, therefore, unavoidable. Accurate estimates of the variance and correlation structure of returns on equities as well as other classes of assets are crucial for portfolio selection, risk management, and pricing of primary and derivative securities.

[1] Two explanations have been put forth for this phenomenon: the leverage effect hypothesis, due to Black (1976) and Christie (1982), and the volatility feedback effect proposed by Campbell and Hentschell (1992) and extended by Wu (2000).

[2] See, for instance, Kroner and Ng (1999), Bekaert and Wu (2001), and Errunza and Hung (1999).

Surprisingly, while there has been a proliferation of conditional econometric models able to capture asymmetry in volatility (see Hentscell (1995) for a synthesis), conditional econometric specifications able to explicitly model asymmetry in covariances and, above all, correlations are far less common. However, as argued by Kroner and Ng (1998), if the expected return on one asset changes due to the occurrence of an asymmetric volatility effect, the correlation (and thus the covariance) between returns on that asset and returns on other assets which have not had a change in their expected returns should also change. Although there exist studies which account for asymmetric effects in conditional covariances, (see, for instance, Braun, Nelson, and Sunier (1995), Koutmos and Booth (1995), Koutmos (1996), Booth, Martikainen, and Tse (1997), Scruggs (1998), and Christiansen (2000)), the econometric methodology employed address the phenomenon through a simplified and not necessarily satisfactorily approach. Apart from the research of Braun *et al.*[3], time-varying covariances are parameterized in the spirit of Bollerslev (1990) where the covariance is proportional to the product of the corresponding conditional standard deviations[4]; the correlation coefficient is the proportionality factor and it is assumed to be constant over the sample period. Although assuming the correlation coefficient constant greatly simplifies the computational burden in estimation, not only there are no theoretical justifications to that assumption and it is also not robust to the empirical evidence.

A second generation of multivariate conditional variance models, where the assumption of constant correlation coefficients is relaxed and asymmetry is explicitly introduced in variances *as well as* covariances, has been introduced by Kroner and Ng. Subsequent applications (see, for instance, Bekaert and Wu (2000), Brooks and Henry (2000), and Isakov and Pérignon (2000)) build on this model. As with most multivariate GARCH model, though, all these representations suffer from a shortcoming: they usually have too many coefficients to estimate, and the models are typically of limited scope or significant parameter restrictions must be imposed.

A second stylized fact which emerges from surveying empirical research is that while the asymmetric phenomenon in (conditional) variances has been widely explored for individual stocks, equity portfolios, and/or stock market indices, day-to-day changes in government bond return volatility has received little attention, instead focusing on the impacts of (macroeconomic) news announcements on conditional volatility of bonds and T-bills.[5] Jones, Lamont and

[3] Braun *et al.*, who analyze a portfolio of two assets, model the second moment matrix by splitting it into three pieces: The two conditional variances associated with each security and the conditional beta. Also in this case conditional covariances do not exhibit explicit asymmetric effects.

[4] The conditional covariances will show an asymmetric response to negative shocks when asymmetric univariate GARCH models are used for the volatilities in the Constant Correlation Coefficient (CCC) model of Bollerslev. However, despite the asymmetric covariances, correlations are constant.

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

Lumsdaine (1998) detect an increase in the conditional bond market variance on days where employment and producer price index data are announced. Li and Engle (1998) examine the effects of macroeconomic announcements on the volatility of US Treasury bond futures. Scheduled announcements trigger strong asymmetric effects: it is shown that whereas positive shocks depress conditional volatility, negative shocks increase it. Christiansen (2000) documents that macroeconomic news releases raise the conditional second moment coefficients of US government bond returns.

The goals of this paper are twofold. First, it is investigated whether, in addition to stocks, government fixed income securities *also* exhibit asymmetry in conditional second moments. Second, this paper explores the dynamics and changes in the correlation of international asset markets, focusing attention on whether the correlation of both bonds and stocks demonstrate evidence of asymmetric response to negative returns. 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. The robust conditional moment test suggested by Kroner and Ng is employed to check whether the model specification adequately characterized the linear dependence shown by the data. We also explore the asymmetric volatility impact of an innovation through "news impact curves" of Engle and Ng (1993), and asymmetry in conditional covariances by the "news impact surfaces" of Kroner and Ng.

We also investigate certain interesting questions: has the formation of the monetary union in Europe increased the correlation among national assets? If national asset correlation has really increased along with the monetary integration, and if the Euro-area is considered more and more as a unified economic-financial block, do investors move capital, which before were allocated within the Euro-area, towards other regions, with obvious consequences on exchange rates? Moreover, what are the consequences of growing asset correlation, if any, on international portfolio diversification? Has the overall return correlation of both bond and equities increased over the latter part of the 1990s and into the early years of the new millennium, as evidenced in Moskowitz (2002) Appendix A provides a brief historical background about the salient steps which have led to the creation of the European Monetary Union (EMU) and it can be used as a reference when answering the above mentioned questions.

We use the Financial Time All-World indices for international equity markets as a measure of overall equity return in a given country and DataStream constructed bond indices as a measure of bond performance to model the covariance structure of world investment markets.

The paper is laid out as follows: section 2 presents a review of the recent literature and describes the stylized facts about financial return GARCH modeling, while section 3 covers the econometric methodology employed in this paper. In section 4, the data used in the paper is described and both unconditional and univariate conditional properties are explored. Section 5 covers the multivariate conditional results and examines the specification and section 6 concludes and discusses areas for further research.

II. Literature Review

As pointed out, among others, by Nelson (1991), the traditional *symmetric* GARCH process introduced by Engle (1982) and Bollerslev (1986) suffers from an important limitation. Although it elegantly captures volatility clustering, it does not allow negative and positive past shocks to have a different effect on future conditional second moments. In other words, only the magnitude, not the sign of lagged innovations determines conditional variance. Therefore a model that captures the asymmetric responses of conditional second moments should be preferable for asset pricing applications. To better see this, consider a portfolio made of equities and what may occur due to a large price drop, like the one that occurred in October 1987. If a negative return innovation generates more volatility than a positive return innovation of the same magnitude, a symmetric GARCH process will underestimate the conditional volatility which occurs after bad news, and similarly will overestimate the conditional volatility following good news. In CAPM-type models, conditional volatility directly affects risk premia investors require to hold risky assets. But the premia forecast by the traditional GARCH differ from those implied by an asymmetric GARCH, with a consequence of probable asset mispricing.

While the univariate GARCH literature began by assuming that return volatility was a linear process of past squared innovations, researchers soon realized that other processes were both better performing and theoretically justified. Three main changes to the stock GARCH model have been made to allow the *news impact curve* (see Engle and Ng (1993)) to take various shapes depending on the evolution of volatility. The first (in terms of significance of impact) was to allow the news impact curve to have different responses to positive and negative innovations. A large number of univariate GARCH models accommodate these effects, including: Exponential GARCH (EGARCH) introduced by Nelson (1991), Asymmetric Power ARCH (APARCH) of Ding, Granger, and Engle (1993), GJR-GARCH of Glosten, Jaganathan, and Runkle (1993), Threshold GARCH (ZARCH) of Zakoian (1994), thereafter extended by Rabemananjara and

Zakoian (1993),[6] just to name a few. The second change to the original news impact curve was to allow the shocks to enter non-linearly (through a Box-Cox like transformation) into the variance. Models which allow this effect include Nonlinear GARCH (NGARCH) of Higgins and Bera (1992) and APARCH. The third major change to the news impact curve has been to allow for a re-centering of the curve, so that the point of no change in the volatility is not necessarily centered at zero; AGARCH (Engle (1990)) and NAGARCH (Engle and Ng (1993)) allow for this type of asymmetry. Hentschell (1995) has proposed a model which encompasses these three effects and provides an overview of the above mentioned univariate asymmetric GARCH parameterization. Recent evidence (Hansen and Lunde (2001)) has shown that not only do these models perform better in-sample, but they also produce superior forecasts.

While asymmetries in conditional volatilities have been thoroughly empirically verified, the efforts to capture asymmetric effects in multivariate settings, however, have been far rarer. Presently, there are only two models capable of capturing asymmetric effects in correlation in a multivariate GARCH model. The first to model asymmetric effects was Kroner and Ng. The model they proposed allows for asymmetric effects in both the variances and covariance. An alternative multivariate GARCH parameterization which permits to capture asymmetries in variances (but not in correlations) is the Dynamic Conditional Correlation (DCC) GARCH model of Engle (2002). As pointed out in Engle and Sheppard (2001), any univariate GARCH model which is covariance stationary and assumes normally distributed errors (irrespective of the true error distribution) can be used to model the variances, as the model is estimated in two steps: the first in which variances are estimated using a univariate GARCH specification, and the second where the parameters of the dynamic correlation are considered. Sheppard (2002) has recently extended the DCC model to allow for asymmetric dynamics in the correlation in addition to the asymmetric response in variances (which were available in the original DCC model). Moreover, while the original DCC model assumed that all assets shared the same news impact curve for correlation, Sheppard's specification is able to accommodate different news impact curves for correlations across distinct assets.

Economically, asymmetric volatility can be explained by two models: leverage effect and time-varying risk premia (volatility feedback). The leverage effect, simply put, states that after a negative shock, the debt-to-equity ratio of a firm has increased. Thus, the volatility of the whole firm, which is assumed to remain constant, must be reflected by an increase in volatility in the

[6] The first version of Zakoian's threshold GARCH appeared in a working paper (CREST, INSEE) dated 1990. This explains why the extension of the model due to Rabemananjara and Zakoian (1993) has an earlier date than the original model published only in 1994.

non-leveraged part of the firm (equity). Christie (1982) was one of the first to provide empirical evidence of the leverage effect, finding a positive correlation between the leverage ratio and the volatility of the firm. An alternative explanation of the larger increase in volatility after a negative shock proffered by Campbell and Hentschel (1992) is that after a negative shock and variance increase, the expected return must become sufficiently high to compensate the investor for the increased volatility, thus creating more volatility (volatility feedback). These two explanations for asymmetries in volatility are not exclusive, and Bekaert and Wu (2000) have combined these two explanations in an empirical model and have shown that the leverage effect *alone* does not adequately explain the changes in volatility after a decrease in the asset price.

Both of these explanations for larger volatility subsequent to a negative shock have primarily focused on the volatility of equities, although the Campbell and Hentschel model is applicable to bonds as well as stocks, through the CAPM, treating bonds as risky assets (see Cappiello, 2000). However, as bonds do not have leverage, the leverage effect is implausible. Further, while there is compelling evidence that bond volatility increases after announcement about macroeconomics news, it is yet to be seen if the asymmetric effect is present in the day to day volatility dynamics of government bonds.

In addition to possible explanations for asymmetries in bond return volatility, little theoretical framework is available to explain the recent evidence of asymmetric response to *joint* bad news in correlations (joint bad news refers to both returns being negative). While certain models can capture these effects, there has been little done to explain their presence. One possible explanation rests on time-varying risk premia. More precisely, if, due to negative shocks, the variances of two securities increase, in a CAPM-type world, investors will require higher returns to compensate the larger risk they face. As a consequence, prices of both assets will decrease and asset correlation will go up, as it usually happens in down markets. Correlation may therefore be higher after a negative than a positive innovation of the same magnitude, indicating its sensitivity to the sign of past shocks. However, this idea has not yet been formalized in a multivariate model. Another plausible explanation is that dependence in returns is higher for large negative returns, and possibly nonlinear. In this case the increased correlation observed is simply a linear approximation to the nonlinear dependence. Recently, Patton (2002) has shown that correlation provides a good approximation to the dependence structure of portfolios of large and small cap stocks. However, it is yet to be seen how widespread this phenomenon is.

III. Econometric Methodology

While there has been wide empirical evidence of asymmetries in volatilities, recent studies (Kroner and Ng (1998), Baekert and Wu (2000), and Cappiello (2000)) have also provided limited evidence for asymmetries in covariance above those which would be present under an assumption of asymmetric volatilities but with constant correlation. In order to investigate the properties of international equity and bond returns, we have chosen to use a recently introduced generalization of the DCC (Engle (2002)) model. The general form of the model employed in this paper was developed in Sheppard (2002), and includes two modifications to the original DCC model: asset specific correlation news impact curves and asymmetric dynamics in correlation.

All DCC class models (including the Constant Correlation Coefficient-GARCH (CCC-GARCH) of Bollerslev (1990)) assume that a $k \times 1$ vector of asset returns r_t are conditionally normal with mean zero and covariance matrix H_t

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

and use the fact that H_t can be decomposed as follows:

$$H_t = D_t R_t D_t, \tag{2}$$

where D_t is the $k \times k$ diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{i,t}}$ on the i^{th} diagonal and R_t is the (possibly) time-varying correlation matrix.[7] The DCC model was designed to allow for two-stage estimation of the conditional covariance matrix H_t: in the first stage univariate volatility models are fitted for each of the assets and estimates of $h_{i,t}$ are obtained; in the second stage asset returns, transformed by their estimated standard deviations resulting from the first stage, are used to estimate the parameters of the conditional correlation. The original DCC estimator had the dynamics of correlation evolving as a scalar process with a single news impact parameters and a single smoothing parameter. However, for higher dimensional models and certain assets, this proved to be inadequate, and the Asymmetric Generalized DCC estimator was developed to capture the heterogeneity present in the data. The model used in this paper is a restricted version of the AG-DCC model.

As asymmetries in volatilities are a widely accepted empirical fact, the univariate volatility models will be selected using the Schwartz Information Criterion (BIC) from a class of

[7] The assumption of conditional normality is not crucial and in the absence of conditional normality, these results have a standard QMLE interpretation.

models capable of capturing the common properties of equity return variance.[8] The following models were included in the specification search (all with one lag of the innovation and one lag of volatility)

- GARCH (Bollerslev (1996))
- AVGARCH (Taylor (1986))
- NARCH (Higgins and Bera (1992))
- EGARCH (Nelson (1991))
- ZARCH (Zakonian (1994))
- GJR-GARCH (Glosten, Jaganathan, and Runkle (1993))
- APARCH (Ding, Engle and Granger (1993))
- AGARCH (Engle (1990))
- NAGARCH (Engle and Ng (1993))

The simplest of the models are GARCH, AVGARCH (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 both differ in that asymmetries in the news impact curve come through re-centering of the curve, instead of a slope change which depends on the sign of past innovations. Appendix C contains exact specification employed for these models.

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

$$Q_t = (1 - a - b)\overline{Q} + a e_{t-1} e'_{t-1} + b Q_{t-1} \tag{3}$$

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

where $\overline{Q} = E[e_t e_t']$ and where a and b are scalars. However, as this model does not allow for asset specific news impact parameters nor asymmetries, the evolution equation has been modified (See Sheppard (2002)) to be

$$Q_t = \left(\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{N}G\right) + A'e_{t-1}e'_{t-1}A + B'Q_{t-1}B + G'n_{t-1}n'_{t-1}G \tag{5}$$

[8] While there are many information criteria available, in addition to likelihood ratio testing using nested models, we felt that the use of the BIC was appropriate as it will lead to asymptotically correct model specification selection.

where A, B, and G are diagonal parameter matrixes, $n_t = I[\varepsilon_t < 0] \circ \varepsilon_t$ (with $\circ$ indicating the Hadamard product), $\overline{N} = E[n_t n_t']$. For $\overline{Q}$ and $\overline{N}$, 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. $Q_t^* = [q_{ii,t}^*] = [\sqrt{q_{ii,t}}]$ is a diagonal matrix with the square root of the i[th] diagonal element of Q_t on its i[th] diagonal position. In other words, Q_t^* is a matrix which guarantees $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$ is a correlation matrix with ones on the diagonal and every other element less than one in absolute value, as long as Q_t is positive definite.[9] The typical element of R_t will be of the form $\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}$. The immediate implication is that R_t will necessarily be a correlation matrix by the Cauchy-Schwartz inequality (see Engle and Sheppard (2001) for a formal proof). Four special cases of this model (equations 3 and 4) exist, the CCC multivariate GARCH $(A, G = [0])$, the DCC multivariate GARCH $(G = [0], A = [a_{ij}] = [\sqrt{a}], B = [b_{ij}] = [\sqrt{b}])$, the asymmetric DCC (ADCC) multivariate GARCH $(A = [a_{ij}] = [\sqrt{a}], B = [b_{ij}] = [\sqrt{b}], \ G = [g_{ij}] = [\sqrt{g}])$, and the generalized diagonal DCC (GDDCC) multivariate GARCH model $(G = [0])$. It is also simple to extend the model to allow for structural breaks in either mean or dynamics. For instance, let d be 0 or 1, depending on whether $t > t < T$. Then to examine whether a structural break has occurred, the model can be modified to

$$\begin{aligned} Q_t = \left(\overline{Q} - d\tilde{Q} - A'\overline{Q}A + dA'\tilde{Q}A - B'\overline{Q}B + dB'\overline{Q}B - G'\overline{N}G + dG'\tilde{N}G\right) + \\ A'e_{t-1}e_{t-1}'A + B'Q_{t-1}B + G'n_{t-1}n_{t-1}'G \end{aligned} \tag{6}$$

where $\overline{Q} = E[e_t e_t'],\ t < t$, and $\tilde{Q} = \overline{Q} - E[e_t e_t'],\ t \geq t$, with $\overline{N}$ and $\tilde{N}$ analogously defined, which is equivalent to the following parameterization (where $\overline{Q}_1 = E[e_t e_t'], t < t$, $\overline{Q}_2 = E[e_t e_t'], t \geq t$) when mean reversion is enforced

$$\begin{aligned} Q_t = \left(\overline{Q}_1 - A'\overline{Q}_1 A - B'\overline{Q}_1 B - G'\overline{N}_1 G\right) + \left(\overline{Q}_2 - A'\overline{Q}_2 A - B'\overline{Q}_2 B - G'\overline{N}_2 G\right) + \\ A'e_{t-1}e_{t-1}'A + B'Q_{t-1}B + G'n_{t-1}n_{t-1}'G. \end{aligned} \tag{7}$$

As the model in equation 6 nests the standard model (equation 3), it is straight forward to test for breaks in the mean of the process. The test can be conducted using standard likelihood ratio tests with k(k-1)/2 d.f. Breaks in dynamics as well as breaks in both dynamics and mean can be tested for analogously (although with different d.f.).

---

[9] Q_t will be positive definite with probability one if $\left(\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{Q}G\right)$ is positive definite.

Kroner and Ng (1998) introduced a notion for multivariate GARCH models analogous to a news impact curve for univariate models, a news impact surface. For the model considered in this paper, the news impact surface for correlation will be asymmetric, having (potentially) greater response to joint bad news (both returns less than zero) than to joint good news. The news impact surface for correlation is given by

$$\begin{array}{ll} f(e_1, e_2) \approx \tilde{c}_{ij} + (a_i a_j + g_i g_j) e_i e_j, & \textit{for} \quad e_1, e_2 < 0 \\ f(e_1, e_2) \approx \tilde{c}_{ij} + a_i a_j e_i e_j, & \textit{otherwise} \end{array}, \qquad (8)$$

where ε_i, $i = 1{,}2$ are the standardized residuals.[10] 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, which can be very different should the models for the univariate volatilities be drastically different, producing asymmetries in covariance in all four directions from the origin.

IV. Data

The data employed for this paper consists of FTSE All-World Indices for 21 countries and DataStream constructed 5 year average maturity bond indices for 13.[11] The FTSE All-World Index Series are a measure of a well diversified investment in a particular country using a value weighted average. These indices are constructed using 90% of the equity value in a country consisting of large- and medium-caps, and represent the total return on equities as the indices are dividend adjusted. The DataStream Benchmark bond indices consist of the most liquid government bonds and follow the European Federation of Financial Analysts (EFFAS) methodology. These bond indices are available daily and are chain linked allowing the addition and removal of bonds without affecting the value of the index. All data were taken from DataStream and converted to US dollar denominated returns (appendix A contains a complete list of the equity and bond indices included in this study). The selected 21 countries contain most of the present day EU, the major markets of the Americas, both developed and developing, and the major markets of Australasia.[12] One of the primary concerns when working with international data, specifically asset correlation, is that non-synchronous trading issues can arise which will

[10] This formula is approximate, due to the non-linear transformation needed. The exact news impact surface is given in appendix C.2.
[11] The actual series were the DataStream Benchmark Bond Indices with 5 years average maturity (code BMXX05Y where XX is the country code).
[12] The 13 included bond markets are a proper subset of the 21 included equity markets and include all of the major world government bond markets.

lead to a downward bias in the estimated correlation. Martens and Poon (2001) have shown that using non-synchronous data results in a significant downward bias in correlation, as compared to *pseudo*-closes.[13] However, with the global scope for this paper, there is never a time when all 21 markets are open. Thus, weekly returns were used instead of daily to alleviate the problem of asynchronous closes.

The data contain 15 years of weekly price observations, for a total of 790 observations from January 2, 1987 until February 15, 2001. All weekly returns were calculated through log differences using Friday to Friday closing prices. To begin analyzing this data set, it is informative to examine the unconditional correlation among the various stock and bond series.[14] Table 1 summarizes information about the distribution of correlations between the equity series, the bond series, and correlations between the equity series and the bond indices, while table 2 (a, b, and c) contains the unconditional correlation for each of the 34 assets. While the distribution of the average correlation for groups of assets is difficult to calculate, we were able to conduct significance test using the bootstrap distributions of these statistics.[15] 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 indicated, it means that the empirical quantile of the bootstrap distribution is less than (or greater than, depending on the test) the statistic.

Overall the assets are reasonably correlated with a median correlation of 0.2986. However, there is a wide range of correlation among the assets, ranging from an average of 0.0808 for US bond index returns to 0.4498 for Dutch equities. Overall, the average correlation for the equity series (.3401) is similar to the overall average correlation for the bond indices (.3270). However, while on average they appear the same, asset returns are highly correlated with their own type and less correlated with the other type, or in other word, the equity-equity and bond-bond correlations are far higher than equity-bond correlations. In fact, median bond-bond return correlation was 0.7276, median equity-equity correlation was 0.4435, and median equity-bond correlation was only 0.1849, with all three means being statistically different from the other two at the 1% level.

[13] *Pseudo*-closes are simply constructed by sampling all prices at the same time GMT.

[14] The unconditional correlation could be considered as a naïve estimate in the presence of heteroskedasticity, and will underestimate the average conditional correlation between the innovations.

[15] While the correlations should be asymptotically multivariate normally distributed, the computation of the asymptotic covariance matrix would be made more difficult as the models are dynamically misspecified requiring an adjustment to the White robust standard errors to account for autocorrelation in the scores of the correlation estimator.

Among the equity index return series, the mean correlation was 0.4137. The equity market with the highest average correlation was The Netherlands with 0.5355 while both Japan and Mexico exhibited the lowest average correlations at 0.2604 and 0.2826 respectively. The intra-stock index return correlations demonstrated a strong increase in correlation when considered at the regional level. In this sample, there exist three clear geographic groups for the data: Australasia, Europe and North America.[16] Within the Australasian subgroup the average correlation was 0.4032, while the average correlation between equity index returns in the Australasian group and the European group was 0.3858, and 0.3052 with North American markets. Average correlation among the European markets was 0.5289, while European and North American markets had an average correlation of 0.3386. Finally, the average correlation within the North American equity markets was 0.4590.[17] The correlations within both the European and American were statistically significantly higher than were the correlations between these two groups and the others. In addition, the correlation within the Australasian group was statistically higher than the correlation between the North American group and the Australasian group.

Turning attention to the correlation between the bond indices, there also appears to be distinct groups for the unconditional correlation of bond returns: Europe, Japan, and North America. Within European bond markets, average correlation between returns was 0.7894, while average correlation between European markets and Japan was 0.4134 and average correlation between European bond index returns and North American bond returns was 0.1508. Correlation among North American bond returns (Canada and the United States) 0.4523 while average correlation between American bond returns and Japanese bond returns was 0.0225.[18] As was the case with the mean equity indices, the mean intra-region correlations were statistically greater than the mean inter-region correlations.

Finally, the average correlation (as per expectations) between the equity index returns and the bond index returns was significantly lower than the intra-stock or intra-bond index return correlation. The mean inter-stock-bond correlation was 0.1500, significantly lower than the average intra-stock correlation of 0.4137 or the average intra-bond correlation of 0.5535. Further, the inter stock-bond correlations were the only subset of the correlation to have *any* statistically significant negative values. In addition, every equity return series had at least one bond index for

[16] Group membership is listed in Appendix C.
[17] The correlation between the US and Canadian equity index returns was 0.6924. The correlation between Canadian and US markets with Mexican equities was much lower, 0.3040 and 0.3806, respectively.

which it was either insignificantly correlated with or significantly *negatively* correlated with. This is clearly an important point in that one would expect efficient portfolios to generally hold both equity and bonds as they provide insurance (although in a limited fashion) against the other. This further confirms that the negative correlation between bonds and equities ubiquitous across nations.

Turning our attention from unconditional second moments to univariate properties of the data, we find that the data possess the standard properties of financial returns. Namely, both bond and stock returns are leptokurtotic, with stock returns having negative skew and bonds, on average, positive skew. Table 4 contains a summary of the univariate statistics for the system.[19] All markets, save New Zealand and Japan produced an average positive return during the sample, with Mexico producing by far the highest average return, annualized at a rate of 21.2%. All save two of the equity index return series were left skewed, with an average skewness of -.68. The raw equity index returns also exhibited extreme excess kurtosis, with an averaging 6.45. It is well know that while heteroskedastic return series can exhibit skewness and fat-tails, returns standardized by their estimated conditional standard deviation can be normal (or close to normal). To investigate the properties of the innovations, we standardized the residuals by the preferred GARCH model (see section 3). While the residuals standardized by their estimated standard deviation are both less skewed (average -.48) and less fat-tailed (averaging 3.05 excess kurtosis), the standardized residuals are highly non-normal. In fact, all 21 equity index return series, even when standardized by an estimated conditional standard deviation, reject normality using a Jarque-Bera test at the 1% level.

Unlike the volatile equity indices, the bond index returns were more homogeneous, having annualized returns ranging from 4.35 to 8.74 with a mean of 6.68 and having uniformly lower standard deviations than the least volatile equity index. Nine of the 13 bond index return series were positively skewed, having an average skewness of 0.21, and were leptokurtotic with an average excess kurtosis of 1.64. The bond index returns standardized by their estimated conditional standard deviations were, again, slightly less skewed, with an average skewness of 0.17 and less fat-tailed, averaging an excess kurtosis of 0.74. As was the case with equity returns, bond index returns typically reject the null of normality. Only the Irish bond index returns do not reject normality at the 5% level using a Jarque-Bera test, with Canadian and French bond index returns also failing to reject the null at the 1% level.

---

[18] Only the average correlation between North American bond returns and Japanese bond returns was insignificantly different from zero (.0382).

[19] Both mean and standard deviation are reported as annualized percent.

Finally to investigate asymmetries in variances and correlation, we can examine if the variance of asset returns are higher after a negative shock than after a positive one. We calculate the $E\left[r_{it}^2 \mid r_{it-1} < 0\right]$ and test the null that $E\left[r_{it}^2 \mid r_{it-1} < 0\right] = E\left[r_{it}^2 \mid r_{it-1} > 0\right]$. If there were an asymmetric increase in the level of variance after a negative shock, we would expect that $\left(\sum_{t=2}^{T} I_{r_{it-1}<0}\right)^{-1} \sum_{t=2}^{T} r_{it}^2 I_{r_{it-1}<0} - \left(\sum_{t=2}^{T} I_{r_{it-1}>0}\right)^{-1} \sum_{t=2}^{T} r_{it}^2 I_{r_{it-1}>0} > 0$. Nineteen of the equity indices had variances after a negative shock greater than after a positive shock, and eleven of these differences were significant at a 10% level, while nine of the bond indices had larger variances after negative shocks, although only one was significant. Following the same line of analysis, we can investigate if the average covariance of the standardized residuals ($E_{t-1}\left[\varepsilon_{it}\varepsilon_{jt}\right] = \rho_{ij,t}$) after joint negative returns is different than after two positive returns by testing $\left(\sum_{t=2}^{T} I_{\varepsilon_{it-1}<0} I_{\varepsilon_{jt-1}<0}\right)^{-1} \sum_{t=2}^{T} \varepsilon_{it}\varepsilon_{jt} I_{\varepsilon_{it-1}<0} I_{\varepsilon_{jit-1}<0} - \left(\sum_{t=2}^{T} I_{\varepsilon_{it-1}>0} I_{\varepsilon_{jit-1}>0}\right)^{-1} \sum_{t=2}^{T} \varepsilon_{it}\varepsilon_{jt} I_{\varepsilon_{it-1}>0} I_{\varepsilon_{jit-1}>0} > 0.$ Every of the equities exhibited significant increases to joint bad news in at least one series, with the United States having the most significant at the 10 level (13), than to joint good news, while only 6 of the bond series exhibited this behavior. Table 3 contains the estimated conditional volatility and conditional correlation for the equity and bond market returns.

V. Empirical Results

The first stage of the model building consisted of fitting the univariate GARCH models for each of the 34 data series and selecting the *best* one using information criteria. Table 5 contains the specification of the GARCH processes selected by the BIC and the estimated parameters from these models. Eighteen of the 21 models selected for the equity return series contained a significant asymmetry term. Of the 18 models with asymmetries, the vast majority (16) preferred the introduction of the asymmetry via the inclusion of threshold effects, with only two preferring a re-centering of the news impact curve (both using the AGARCH model). As widespread as the evidence of asymmetry volatility was in the equity series, it was equally absent from the bond index return series. Only 3 of the 13 models selected exhibited asymmetric effects, all of the threshold variety. This is consistent with the earlier evidence of little conditional difference in variances after negative shocks for bond returns. Interestingly, though, as explained below, bond (as well as equity) returns exhibit asymmetry in conditional correlation. Figure 1 contains the news impact curves for five of the assets. The dramatically different shapes highlight the flexibility of this modeling approach. For instance, the model selected for Swiss equity returns was an EGARCH with a negative parameter on the innovation and a positive parameter on absolute value of the innovation resulting in a news impact curve which is extremely asymmetric, indicating a much smaller increase in volatility after a positive shock. Likewise, the news impact curve for Canadian bond return volatility is near zero for all positive shocks and only increases for negative ones, while the Swiss bond returns show an asymmetric response to *good* news with a larger increase in volatility subsequent to a positive shock.

Four different models were estimated for the dynamics of the correlation. The first, and simplest model, was a standard scalar DCC (i.e. each of the matrices, A and B, are diagonal with the same value on each diagonal element and no asymmetric terms are included). Next the full diagonal version of the model was estimated allowing for no asymmetries in the correlation dynamics. The two forms of model estimated were an asymmetric DCC model (A, B and G each consist of a single unique element) and the full diagonal version of this model where asymmetric terms were introduced allowing for different news impact and smoothing parameters across the assets. Upon inspection of the fit correlation and the data, it became obvious that a large number of the series have undergone a significant structural break when the exchange rates were irrevocably fixed. In order to correct for this obvious deficiency, all of the 4 base models were modified to allow for a structural break in the mean and for both a structural break in the mean and in the dynamics across the introduction of the Euro. Tables 6 and 6a contains the results of the estimated models, with the results presented for the parameters of the models where the mean was allowed to change but not the dynamics. Almost all of parameters in the models estimated were significant, with exceptions noted in the table. The first observation is that the diagonal versions of the models significantly outperform the scalar versions of the same model. In addition, both of the asymmetric DCC models outperform their non-asymmetric DCC counterparts, with p-values of zero. The shocks to correlation were typically highly persistent, with a half-life of more than 14 weeks for the simplest symmetric scalar DCC model. For the diagonal DCC model, two of the assets series exhibited no (or nearly no) innovation, and for those which did, the half-life of the innovation ranged from 9 to over 63 weeks. In order to calculate the expected half life of an innovation for the asymmetric model, it is necessary to use expected value or by assuming symmetry for the distribution. Overall, the asymmetric models produces slightly less persistence, but were also highly persistent.

We also found significant evidence of a structural break when the EMU exchange rates were irrevocably fixed[20]. We tested for both a structural break in the mean and a structural break in both the mean and the dynamics. The likelihoods of these 12 models (3 treatments of the original 4 models) are in Table 6a. We overwhelmingly reject the null of no structural break in the mean for all models (typical likelihood ratios were approximately 1800 with 561 degrees of freedom), yet find no compelling evidence for both a break in the mean and the dynamics. In addition, allowing for a break reduced the persistence of the series to typically 3 to 10 weeks. We see this as further evidence in support of the break, as series with unconditional shifts are known to produce longer memory that properly modeled series. The remainder of the paper will present the AG-DCC model with a break in the mean but not in the dynamics. Figures 2 and 3 contain news impact *surfaces* for German-US equity correlation and covariance respectively. The correlation news impact surface is highly asymmetric, showing a larger response to in the -- quadrant news than in the ++ quadrant (i.e. more responsive to joint bad news than to joint good news of the same magnitude). However, when the correlation and volatilities are simultaneously considered, the asymmetry becomes even more striking, with a huge increase for joint negative shocks, little change even for larger positive shocks, and asymmetries in all 4 quadrants.

V.1 Specification Testing

In order to verify if the specification selected adequately explains the dynamics in the data, we made us of the robust conditional moment tests (Wooldridge (1990, 1991)). The test is useful in detecting whether a variable (or a function of that variable) is useful in predicting a *generalized* residual $u_{ij,t}$ (a generalized residual is a constructed residual, such as $u_t = r_{it}^2 - h_{it}$ or $u_t = \left(r_{it}^2 / h_{it}\right) - 1$, which should have conditional expectation zero). This resulting statistic tests if a set of moment conditions, $x_{g,t-1}$, can predict the generalized residual series. The test statistic is given by

$$C = \left[(1/T) \sum_{t=1}^{T} u_{ij\,t} \lambda_{g,t-1} \right]^2 \left[(1/T) \sum_{t=1}^{T} u_{j\,t}^2 \lambda_{g,t-1}^2 \right]^{-1} \qquad (9)$$

[20] While it would be ideal to test each series for a break at all points in time, it is infeasible to follow this course as the parameters of the model will not be identified under the null of no break, making standard testing theory incorrect. The choice of allowing the break to occur at the introduction of the Euro was driven by the expected increase in correlation among EMU countries, and possible increases in other countries toward the end of the sample.

where $l_{g,t-1}$ is the residual from a regression of the moment conditions on the scores of the likelihood. Under mild regularity conditions, C is asymptotically distributed $c_{(1)}$. The test is relatively simple to compute, as it can be conducted using two regressions: the first where the moments are regressed on the scores of the estimated model, and the second where a vector of ones is regressed on the product of the generalized residuals and the residuals from the first regression. The moment conditions can be any function of any variable in the conditioning set. However, in order to keep the analysis tractable, we focus on a few types of potential misspecification. The first and simplest is whether the sign of a lagged return can predict future volatility. In other word, $x_{it-1} = I[r_{t-1} < 0]$ is a binary variable that indicates whether the past return was negative. Analogously, we can construct variables which measure a positive impact, or whether the signed magnitude of a past innovation can predict future volatility. In examining the volatility models, we used 4 different criteria.

$$
\begin{aligned}
x_{1t-1} &= I[r_{t-1} < 0] \\
x_{2t-1} &= I[r_{t-1} > 0] \\
x_{3t-1} &= r_{t-1}^2 I[r_{t-1} < 0] \\
x_{4t-1} &= r_{t-1}^2 I[r_{t-1} > 0]
\end{aligned}
\tag{10}
$$

In testing the volatility models selected, 34 x 34 x 4 (4624) tests were conducted (34 generalized residual series, 34 potential series to get the moment conditional from, and 4 different moments to choose from). The generalized residual was defined as $u_{i,t} = r_{i,t}^2 - h_{i,t}$. The overall rejection rate was extremely close to size at 0.0705 using a size of 5%. However, the rejection rate for bonds was higher than the rate for equities, with the majority of the bond rejections resulting from misspecification tests using equity returns as moment indicators indicating that equity return volatility may spill over to bond markets possibly through a flight to quality. Table 7 contains more detailed information on the types of rejections and the rejection for bonds and stocks as groups.[21]

We also tested the correlation estimates by stacking the T x k x *(k-1)/2* generalized residuals $u_{ij,t} = e_{i,t} e_{j,t} - r_{ij,t}$ (the outer product of the standardized residuals minus the estimated correlation) using the following 8 moment conditions (for each of the 33 x 17 off diagonal series):

[21] We also tested the generalized residuals against only moments created using their own lagged data, and found the rejection rate was significantly under size at 0.0074.

$$
\begin{aligned}
x_{5t-1} &= I\left[\varepsilon_{i,t-1} < 0\right] I\left[\varepsilon_{j,t-1} < 0\right] \\
x_{6t-1} &= I\left[\varepsilon_{i,t-1} > 0\right] I\left[\varepsilon_{j,t-1} < 0\right] \\
x_{7t-1} &= I\left[\varepsilon_{i,t-1} < 0\right] I\left[\varepsilon_{j,t-1} > 0\right] \\
x_{8t-1} &= I\left[\varepsilon_{i,t-1} > 0\right] I\left[\varepsilon_{j,t-1} > 0\right] \\
x_{9t-1} &= \varepsilon_{i,t-1}\varepsilon_{j,t-1} I\left[\varepsilon_{i,t-1} < 0\right] I\left[\varepsilon_{j,t-1} < 0\right] \\
x_{10t-1} &= \varepsilon_{i,t-1}\varepsilon_{j,t-1} I\left[\varepsilon_{i,t-1} > 0\right] I\left[\varepsilon_{j,t-1} < 0\right] \\
x_{11t-1} &= \varepsilon_{i,t-1}\varepsilon_{j,t-1} I\left[\varepsilon_{i,t-1} < 0\right] I\left[\varepsilon_{j,t-1} > 0\right] \\
x_{12t-1} &= \varepsilon_{i,t-1}\varepsilon_{j,t-1} I\left[\varepsilon_{i,t-1} > 0\right] I\left[\varepsilon_{j,t-1} > 0\right]
\end{aligned}
\tag{11}
$$

This results in a total of 8 x 17 x 33 (4488), one for each of the 8 moment indicators for each of the above diagonal elements of R_t. Table 8 contains the percentage rejection for these tests. Overall the rejection rate was near size at 0.0533, and across the 8 moment indicators, the performance was relatively equal, with no single indicator causing a disproportionately large number of rejections. Based on the robust conditional moment test, we feel the AG-DCC model with a break in the mean adequately describes the data.

V.2 Volatility Dynamics and Linkages

While each of the volatility series was assumed to evolve independently of the other series, the model allows us to examine the volatility linkages across the countries. A simple criterion to examine these linkages is the correlation between the estimated volatilities of two assets:

$$
\rho_{h_{it}h_{jt}} = \frac{\sum_{t=1}^{T}\left(h_{it} - \bar{h}_i\right)\left(h_{jt} - \bar{h}_j\right)}{\sqrt{\sum_{t=1}^{T}\left(h_{it} - \bar{h}_i\right)^2 \sum_{t=1}^{T}\left(h_{jt} - \bar{h}_j\right)^2}} \tag{12}
$$

Overall, the volatilities of the equity markets were reasonably correlated, with an average correlation of 0.3245, and were similar both pre- and post-introduction of the fixed exchange rate regime system in Europe. However, there were strong regional effects in the linkages. For instance, the correlation of the volatility of European equity market returns was 0.5457 over the entire sample, and was also similar across the introduction of the euro. The American equity markets' volatilities were also extremely correlated, averaging 0.6115, while the correlation between US and Canadian equity volatility was extremely high at 0.7963. Australasian equity volatility correlation was similar to the over all average at 0.4175, although this was in part due to extremely low correlation between the volatilities of New Zealand with the rest of this group. As was the case with equity returns, correlation of equity volatilities are much lower across group than within. Also not surprising, the correlation among the volatilities of larger markets was higher with volatility between France, Germany, and US, and the UK equity markets averaging 0.7062.

Figure 4 contains a plot of the annualized average volatility series for 4 groups of equities: European, 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 Gulf war in 1990/91, during the financial crisis which gripped Russia, Southeast Asia, and Latin America in 1997/98, when signs of a slowdown in the world economy started to affect equity markets in March 2001, and when terrorist attacks hit the US in September 2001. Interestingly, volatility increased for European Union countries in 1992 and 1993, when there was tension within the European Monetary System with resulting interest rate increases and exchange rate realignments.

Similarly, bonds volatility demonstrated low global correlation when considered on a global scale, but regional linkages in bond return volatility were strong. The overall average correlation between bond return volatilities was 0.3515, while correlation between European bond volatilities was 0.5303 and among EMU member countries was 0.7951. Correlation between bond market volatility in the Americas was a low 0.2904.[22] Average correlation between the volatility series of the bond returns and the volatility of the equity returns was, unsurprisingly, lower, at 0.1815. Figure 5 contains a plot of the annualized average bond return volatility in the EMU countries, the U.S, and Japan. The bond markets are much less volatile than the equity markets, and demonstrate less clear linkages in volatility. For instance, none of the clear increases in equity volatility found in the equity series can be seen simultaneously in all the bond volatility series. However, October '87 is evident in the U.S. series, the friction in the EMU can be seen in its series, and the Asian financial crisis is obvious in Japanese bond volatility series. All these episodes point towards a "flight to quality phenomenon", with investors moving capital from equities to bonds. Yet these significant events do not spread as they did with equities.

In order to ensure that the correlations, especially any changes after the introduction of the fixed exchange rate system, were actually changing, and were not simply the result of a change in volatility, we also tested the volatility models for structural breaks in the level (through an inclusion of a dummy variable on the constant) of volatility and in both the level and the dynamics.[23] Testing with a likelihood ratio, we were able to reject the null of no structural breaks in 6 out of the 21 series. However, using a consistent information criterion such as the BIC, we

[22] The US bond market volatility was basically uncorrelated with every other bond market volatility with the exception of Canadian bond volatility.

never selected a model with breaks of either type over the simpler models for any of the 34 data series, with the exception of Italian equities.

V.3 Correlation Dynamics

Interesting empirical observations about volatility notwithstanding, the primary motivation of this paper was to examine the correlation dynamics of international equity and bond returns. There appear to be significant variations in the correlations of these assets during the time period of the sample. Figure 6 contains a graph of the estimated dynamic equity correlation between three countries within the EMU, namely France, Germany, Italy, and Great Britain. The correlation has clearly increased between all four of these countries since the introduction of the Euro (indicated by the dashed line). The adoption of a common monetary policy and the consequent irrevocable fixing of exchange rates for EMU countries have led to much higher correlations between equity returns not only in the three countries which are in the EMU, but also the U.K. The increase between France, Germany, and Italy has, however, been more marked, evidenced by an increase from an average of 0.6196 to 0.8515 for France-Germany, 0.4615 to 0.8249 for France-Italy, and from 0.4469 to 0.8117 for Germany-Italy when comparing the pre- and post-Euro periods. The correlation increase is so striking that not only is a mean change obvious, but correlations appear to be less volatile after the introduction of the euro. The correlation between Great Britain and the three EMU countries has also increased, although to a slightly lower level, with an average correlation between the U.K. and the three EMU countries rising form an average of 0.4629 to 0.6797.

Figure 7 contains the average equity correlations for the EMU countries, Europe without the EMU countries, the Americas, and Australasia. October '87 stands out as a clear increase in correlation across the four groups, with ubiquitous spikes in the correlation in all six series. While there appear to be increase in the correlation between the EMU, Europe without the EMU, and the Americas, there do not appear to be large breaks in the average conditional correlation between any of these three and Australasia, with the possible exception of Americas-Australasia correlation at the fixing of the exchange rates in 1999, although this is most likely not due explicitly to the Euro. The general increases seen, especially between Europe and the Americas may be due to one of two causes: globalization and MNCs or TMT companies. With the major run-up of technology stocks in the late '90s and subsequent let down, many value weighted indices became heavily weighted with technology companies. This, in turn, let correlation among

[23] We assumed the specification of the model dynamics remained constant when testing for structural breaks in the parameters.

value0weighted equity return indices go up due to a changing mix of sectors, with technology getting a very large weight. When the bubble burst, technology companies all over the world saw large decreases in value, which may have led to a general increase in correlation on top of the euro effects. The investigation of this idea, however, is beyond the scope of this paper.

Figure 8 contains graphs of average correlation equity return *within* groups. There appear to be mild linkages in correlation among the groups, although these linkages appear stronger in periods where there is identifiable bad news, most notably October 1987 and September 2001. Both the EMU countries and European countries in general appear to have had a mild increase in the unconditional level of correlation following the fixing of the exchange rate in 1999, although there is also some evidence that the increase may have been partially anticipated with a slow, but steady increase beginning about 1997 for EMU countries. Further, as evidenced earlier, many of the EMU countries have seen an extreme increase in correlation among equity returns implying that the increase is not uniform across the EMU; there may be a divergence between the dominant EMU equity markets and the lesser ones. The equity returns of the Americas have also had a notable increase in correlation beginning in late 90s and continuing until the present, again possibly due to technology companies. The correlation with in the Australasia group remains basically unchanged during the late 90s.

Bond market correlation dynamics contained both similarities and dissimilarities to equity market correlation dynamics; similar in that there have been some radical changes since the introduction of the fixed exchange rate regime, and dissimilar in that linkages across regions appear to be much weaker. Figure 9 contains the average equity return correlation between the EMU, the remainder of Europe, and the American bond markets. The average correlation between European equity returns within the EMU and those not in the EMU appears to have increased slightly, however correlation between American markets and EMU markets has also increased sharply after the fixed exchange regime went into effect. Finally, the average correlation between European non-EMU member countries and the Americas also appears to have increased. It is important to note that while the correlation between the American and both of the European groups' bond returns has increased in the latter portion of the '90s and into the new millennium, the levels are still very different. The correlation between bond returns in Europe is typically 0.7, which the correlation between either of the European groups and the Americas is typically less than half, averaging near 0.3. This is unsurprising given the many common economic factors which affect European countries both within and outside of the EMU and help dictate monetary policy.

Figure 10 contains the plot of bond market correlations with three groups: the EMU countries, Europe without the EMU countries, and the Americas. The most striking conclusion from these pictures is that, beginning approximately 15 weeks before the exchange rates became fixed until the present, EMU bond market returns have been basically perfectly correlated, remaining above 0.96 for the duration. The synchronization of monetary policy necessary for the effective creation of the Euro has undoubtedly caused this phenomenon. However, the correlation among European non-EMU members has remained in the same range it has always been in. Unlike equity market returns, correlation among bond returns in the Americas (Canada and the U.S.) have been fairly constant. Again, it is important to notice that the levels are different in the pictures, with EMU countries having a very high historical correlation (most likely due to some of the failed attempts at managing exchange rates detailed in Appendix A), European non-EMU countries that are also highly correlated, although less than the EMU countries, and the Americas that are much less correlated than either of these groups. Figure 11 contains the bond return correlation between three of the largest providers of government bonds: Germany, Japan, and the U.S. The correlation between German and Japanese bond returns plummeted with the introduction of the fixed exchange rate regime, form a fairly significant 0.5 to an average near zero.[24] At the same time, bond market returns have become increasingly correlated between the German and U.S. bond markets, indicating a possible coordination and responsiveness to monetary policy by both the ECB and the FED or at least stronger common shocks. U.S. and Japanese bonds correlation has remained in a fairly narrow range for the entire sample, averaging near zero.

Finally, figures 12 and 13 contain plots of the average correlation between the various equity markets and the EMU bond returns and American bond returns, respectively. Not surprisingly, EMU bond returns are relatively highly correlated with EMU equity returns (Figure 12) while correlation between EMU bond returns and American and Australasian equity returns is typically near zero and often negative, although both of these correlation remain in a relative narrow band. If it has had any effect, the introduction of the Euro has led to a decrease in the correlation between EMU bond returns and equity returns in other regions. One notable decrease is evident in all three pictures: October 1987, providing strong evidence to a flight-to-quality. The levels notwithstanding, the dynamics of the three series are remarkably similar, yet this

[24] In fact, the decrease began slightly before the introduction of the fixed exchange rates. In the fourth week of October 1998, after months of carry trades involving borrowing at near zero interest rates in Japan, investing in the U.S., the Japanese central bank intervened against rising interest rates (while trying to encourage the economy) by buying bonds, causing the carry trade to unravel. In fact, the standardized return on Japanese bonds was 6 standard deviations this week.

similarity is most likely due to the equity return correlation dynamics. Figure 13 paints an analogous picture for American bond returns, where the American bond returns have the highest mean correlation with American equities (although similar to the mean with the EMU equities) and have a much lower mean with Australasian equity returns. Again, the dynamics are similar with all having a strong reaction in October 1987, and a slow but steady decline over the few years.

VI. Conclusion

In this paper we found strong evidence of asymmetries in conditional covariance of both equity and bond returns, although the asymmetries are present in markedly different manners. Asymmetric DCC models are uniformly preferred to their symmetric counterparts using likelihood ratio testing, and asset specific news impact curves and smoothing parameters to the pooled parameter of a scalar DCC. While widespread evidence was found that national equity index return series show asymmetry in conditional volatility, little evidence was found indicating asymmetry in bond index return volatility. However, despite the lack of evidence of asymmetric conditional volatilities, bonds (as well as equities) exhibit asymmetry in conditional correlation, although, equities showed a stronger response to joint bad news than bonds do. Strong evidence of market volatility correlation is also presented for equity returns: in particular, annualized average volatility series for European, EMU, American and Australasian equities show linkages during easily identifiable periods of financial turmoil such as the crash of '87, the beginning o of the Gulf war, and the Asian financial crisis. Again, unlike equity returns, bond market volatilities demonstrate less clear linkages, instead, exhibiting increases to region specific events which do not appear to be contagious across regions.

Upon the creation of the Euro, initially without a circulating currency when EMU exchange rates were irrevocably fixed, 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 correlation for the major markets of Europe, i.e. France, Germany and Italy (which are part of the EMU) and UK (which is not part of the EMU), has increased since the introduction. In addition to the expected increase in the Euro-area, evidence is also found of a meaningful increase in correlation of other markets with the EMU nations, possibly signaling stronger economic ties. Further, the introduction of a fixed exchange rate regime has led to near perfect correlation among bond returns within EMU countries, which is not surprising in consideration of the monetary policy harmonization within the EMU. This increase in correlation among asset returns within the EMU area may have induced investors, when diversifying their portfolios, to move capital from Europe to the US, possibly contributing to the depreciation of the euro vis-à-vis the US dollar in the months following the introduction for the fixed rate regime.

Conditional equity correlation series among regional groups is found to increase dramatically when bad news hit financial markets. This is am important implication for international investors; 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 usually 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. In other words, not only is equity-bond return correlation typically low, it actually is lower during periods of financial turmoil. The findings of this paper have crucial implications for practical international investing. While high correlation can become low correlation by taking short positions, many large investors are prohibited or severely limited in the amount of short position they may hold. Further, holding assets in a portfolio which may have a negative expected return is typically undesirable. The lowest correlations found were typically between equity returns in one country and bond returns in another. This unsurprising yet undocumented observation should provide guidance for investors seeking to maximize diversification without taking short positions.

The volatility and especially correlation dynamics documented in this paper raise significant issues for both theoretical finance and investors. For instance, can the risk of increasing correlation due to market declines (exactly when correlation becomes a very bad thing) 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?

Appendix A: Historical background of the EMU

This appendix describes the essential steps which have led to the creation of the European Monetary Union (EMU). After the collapse of the Bretton Wood system, in the spring 1972, the European Economic Community (EEC) countries created the so-called "snake" in the "tunnel": EEC exchange rates were allowed to fluctuate within restricted margins (±1.125% - the snake) around par value, but maintained wider margins (±2.25% - the tunnel) around the parities vis-à-vis non-partner countries. Balance of payment difficulties led some countries to leave the snake and the remaining members agreed, in March 1973, for a joint float: while maintaining fixed parities with predetermined margins among themselves, they let their currencies float against the US dollar. By 1975, however, the principle of somehow fixed exchange rates was dead.

A later attempt to create a currency area was undertaken in 1979, when the EEC countries (except for Britain) created the European Monetary System (EMS), which was based on the Exchange Rate Mechanism (ERM) and the European Currency Unit (ECU). As for the ERM, once bilateral parities were declared, actual exchange rates could oscillate around them within predefined margins (±2.25%, widened to ±15% from August 1993). Central parities could be modified only by collective agreement and member countries were obliged to intervene in foreign exchange markets when a margin was hit. The ECU differentiated the EMS from the old snake, in that the creation of this common currency unit was the premise to a monetary union. The EMS was characterized by broad exchange rate stability from January 1987 to August 1992, but also by massive speculative attacks against the Italian lira, the British pound and the French Franc (summer 1992 and 1993).

The Maastricht Treaty (signed in February 1992) laid out three stages which have led to the EMU. In the first stage (1990-1993), which in fact started before the Treaty, several measures were introduced, among which the abolition of restrictions to capital movements and the prohibition of financing public deficit through central banks. The second stage (1994-6/8) established, among other measures, a control of the public deficit (to be reduced to 3% of GDP) and debt (to be not higher than 60% of GDP) as well as the constitution of the European Monetary Institute (EMI), which was supposed to coordinate monetary policies. The second stage was essentially designed to secure convergence of the EEC countries and allow the introduction of a single currency. Member participants were supposed to meet a number of convergence criteria, among which: an inflation rate not larger than 1.5% the inflation rate of the three best performing countries, i.e. those with the lowest inflation rates; a long-term interest rate not larger than 2% the average interest rate of those same three countries; an exchange rate within the fluctuation margins in the last two years. In the third stage, which begun in January 1999, the European Central Bank (ECB) was created, bilateral exchange rates were irrevocably fixed and the euro has been replacing the single national currencies. On January 1 1999 bilateral exchange rates between member countries were irrevocably fixed (as well as those vis-à-vis the ECU), while the European single currency changed its name from ECU into euro. The euro, which first was a non-circulating currency, began to circulate from January 1 2002, and it will be totally replacing the national currencies from July 1 2002 at the latest.[25]

[25] The countries which are part of the European Monetary Union are: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain.

Appendix B: Countries Selected

Europe	Australasia
• AUSTRIA*	• AUSTRALIA
• BELGIUM*	• HONG KONG
• DENMARK*	• JAPAN*
• FRANCE*	• NEW ZEALAND
• GERMANY*	• SINGAPORE
• IRELAND*	
• ITALY	**Americas**
• THE NETHERLANDS*	• CANADA*
• SPAIN	• MEXICO
• SWEDEN*	• UNITED STATES*
• SWITZERLAND*	
• NORWAY	
• UNITED KINGDOM*	

* indicates bond data included for these countries.

Appendix C: Exact Specifications

C.1 Univariate GARCH models

While some of the models differ in the exact representation originally proposed, the qualitative features remain unchanged. The models were changed to improve comparability across models.

GARCH

$$h_t = w + a e_{t-1}^2 + b h_{t-1}$$

AVGARCH (Absolute Value)

$$h_t^{1/2} = w + a\,|e_{t-1}| + b h_{t-1}^{1/2}$$

NARCH (Non-linear)

$$h_t^{l/2} = w + a\,|e_{t-1}|^l + b h_{t-1}^{l/2}$$

EGARCH (Exponential)

$$\log(h_t) = w + a\frac{|e_{t-1}|}{\sqrt{h_{t-1}}} + g\frac{e_{t-1}}{\sqrt{h_{t-1}}} + b\log(h_{t-1})$$

ZARCH (Threshold)

$$h_t^{1/2} = w + a\,|e_{t-1}| + gI[e_{t-1} < 0]\,|e_{t-1}| + b h_{t-1}^{1/2}$$

GJR-GARCH

$$h_t = w + a e_{t-1}^2 + gI[e_{t-1} < 0] e_{t-1}^2 + b h_{t-1}$$

APARCH (Asymmetric Power)

$$h_t^{l/2} = w + a\,|e_{t-1}|^l + gI[e_{t-1} < 0]\,|e_{t-1}|^l + b h_{t-1}^{l/2}$$

AGARCH (Asymmetric)

$$h_t = w + a(e_{t-1} + g)^2 + b h_{t-1}$$

NAGARCH (Nonlinear Asymmetric)

$$h_t = w + a(e_{t-1} + g\sqrt{h_{t-1}})^2 + b h_{t-1}$$

C. 2 New Impact Surface for correlation

$$f(e_1, e_2) = \frac{\tilde{c}_{ij} + (a_i a_j + g_i g_j) e_i e_j + b_i b_j r_{ij,t}}{\sqrt{(\tilde{c}_{ii} + (a_i^2 + g_i^2) e_i^2 + b_i^2)(\tilde{c}_{jj} + (a_j^2 + g_j^2) e_j^2 + b_j^2)}} \qquad , for \quad e_1, e_2 < 0$$

$$f(e_1, e_2) = \frac{\tilde{c}_{ij} + a_i a_j e_i e_j + b_i b_j r_{ij,t}}{\sqrt{(\tilde{c}_{ii} + (a_i^2 + g_i^2) e_i^2 + b_i^2)(\tilde{c}_{jj} + a_j^2 e_j^2 + b_j^2)}} \qquad , for \quad e_1 < 0, e_2 > 0$$

$$f(e_1, e_2) = \frac{\tilde{c}_{ij} + a_i a_j e_i e_j + b_i b_j r_{ij,t}}{\sqrt{(\tilde{c}_{ii} + a_i^2 e_i^2 + b_i^2)(\tilde{c}_{jj} + (a_j^2 + g_j^2) e_j^2 + b_j^2)}} \qquad , for \quad e_1 > 0, e_2 < 0$$

$$f(e_1, e_2) = \frac{\tilde{c}_{ij} + a_i a_j e_i e_j + b_i b_j r_{ij,t}}{\sqrt{(\tilde{c}_{ii} + a_i^2 e_i^2 + b_i^2)(\tilde{c}_{ij} + a_i^2 e_i^2 + b_i^2)}} \qquad , for \quad e_1, e_2 > 0$$

Bibliography

Ang, A. and G. Bekaert, 1999, "International Asset Allocation with Time-Varying Correlations," *NBER Working Papers 7056*, National Bureau of Economic Research, Inc. 1999.

Bekaert, G, and G. Wu, 2000, "Asymmetric Volatility and Risk in Equity Markets," *Review of Financial Studies*, Vol. 13 (1), pp. 1-42.

Black, F., 1976, "Studies of Stock Prices Volatility Changes," *Proceeding from the American Statistical Association, Business and Economics Statistics Section*, pp. 177-181.

Bollerslev, T., 1986, "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, Vol.31, pp.307-327.

Bollerslev, T, 1990, "Modeling the Coherence in Short Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model," *Review of Economics and Statistics*, Vol.72, No.3, pp.498-505.

Booth, G. G., T. Martikainen, and Y. Tse, 1997, "Price and Volatilities Spillovers in Scandinavian Stock Markets", *Journal of International Money and Finance*, Vol. 21, June, 811-823.

Braun, P. A., D. B. Nelson, and A. M. Sunier, 1995, "Good News, Bad News, Volatility, and Betas," *Journal of Finance*, 50, pp. 1575-1603.

Brooks, C., and U. T. Henry, 2000, "Linear and Non-Linear Transmission of Equity Return Volatility: Evidence from the US, Japan and Australia," *Economic Modeling*, 174, pp. 497-513.

Campbell, J. Y., and L. Hentschell, 1992, "No News Is Good News," *Journal of Financial Economics*, 31, pp. 281-318.

Cappiello, L., 2000, "Do Fixed Income Securities Also Show Asymmetric Effects in Conditional Second Moments?," *FAME working paper*, # 12, Geneva, Switzerland.

Christiansen, C., 2000, "Macroeconomic Announcement Effects on the Covariance Structure of Government Bond Returns," *Journal of Empirical Finance*, 75, pp. 479-507.

Christie, A., 1982, "The Stochastic Behavior of Common Stock Variances," *Journal of Financial Economics*, 10, 407-432.

Das, S., and R. Uppal, 2001, "Systemic risk and international portfolio choice," Manuscript, Harvard University.

De Santis, G. and B. Gerard, 1997, "International Asset Pricing and Portfolio Diversification with Time-Varying Risk," *Journal of Finance*, 52, 1881-1912.

Ding, Z., R. F. Engle and C.W.J. Granger, 1993, "A Long Memory Property of Stock Market Returns and a New Model," *Journal of Empirical Finance*, Vol. 1, pp. 83-106.

Engle, R. F., 1982, "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation," *Econometrica*. Vol. 50, pp. 987-1008.

Engle, R. F., 2002, "Dynamic Conditional Correlation - A Simple Class of Multivariate GARCH Models," Forthcoming in *Journal of Business and Economic Statistics*.

Engle, R. F., and L. Li, 1998, "Macroeconomic Announcements and Volatility of Treasury Futures," *UCSD Working Paper* No. 97-27.

Engle, R. F., and V. Ng, 1993, "Measuring and Testing the Impact of News On Volatility," *Journal of Finance*, Vol. 48, pp. 1749-78.

Engle, R. F., and K. Sheppard, 2001, "Theoretical and Empirical Properties of Dynamic Conditional Correlation MVGARCH", *UCSD Working Paper* No. 2001-15.

Erb, C., C. R. Harvey, and T. Viskanta, 1994, "National Risk and Global Fixed Income Allocation," *Journal of Fixed Income*, pp. 17-26.

Errunza, V., K. H. and M.-W. Hung, "Can the Gains from International Diversification be Achieved without Trading Abroad?," *Journal of Finance*, 1999, Vol. 54, pp. 2075-2107.

Glosten, L., R. Jagannathan, and D. Runkle, 1993, "Relationship Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *Journal of Finance*, Vol. 48, pp. 1779-1801.

Hansen, P. R., and A. Lunde, 2001, "A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH(1,1)," *Brown University Working Paper* No. 01-04.

Hentschel, L., 1995, "All in the family: Nesting symmetric and asymmetric GARCH models," *Journal of Financial Economics*, Vol. 39, pp. 71-104.

Higgins, M. L., and A. K. Bera, 1992, "A Class of Nonlinear ARCH Models," *International Economic Review*, 33, pp. 137-158.

Isakov D. and C. Pérignon, 2000, "On the dynamic interdependence of international stock markets : A Swiss perspective," *Swiss Journal of Economics and Statistics*, Vol. 136, No. 2, pp. 123-146.

Koutmos, G., and G. G. Booth, 1995, "Asymmetric Volatility Transmission in International Stock Markets," *Journal of International Money and Finance*. Vol. 14, No. 6, pp. 747-62.

Koutmos, G., 1996, "Modeling the Dynamic Interdependence of Major European Stock Markets," *Journal of Business, Finance, and Accounting*, 23, pp. 975-988.

Kroner, K. F., and V. K. Ng, 1998, "Modeling asymmetric comovements of assets returns," *Review of Financial Studies.* Vol. 11, No.4, pp 817-44.

Jones, C., O. Lamont, and R. Lumsdaine, 1998, "Macroeconomic News and Bond Market Volatility," *Journal of Financial Economics*. March, pp. 315-27.

Longin, F., and B. Solnik, 2002, "Extreme Correlation of International Equity Markets," Forthcoming in *The Journal of Finance.*

Marten, M. and S.-H. Poon, 2001, "Return Synchronization and daily correlation dynamics between international stock markets," *Journal of Banking and Finance*, Vol. 25, pp. 1805-27.

Moskowitz, T., 2002, "An Analysis of Covariance Risk and Pricing Anomalies," Manuscript, Graduate School of Business, University of Chicago.

Nelson, D. B., 1991, "Conditional Heteroskedasticity in Asset Returns: A new approach," *Econometrica,* Vol. 59, pp. 347-70.

Patton, A. 2001, "On the Importance of Skewness and Asymmetric Dependence in Stock Returns for Asset Allocation," Manuscript, UCSD.

Scruggs, John T., 1998, "Resolving the Puzzling Intertemporal Relation between the Market Risk Premium and Conditional Market Variance: A Two-Factor Approach," *Journal of Finance,* Vol. 53, pp. 575-603.

Sheppard, K., 2002, "Understanding the Dynamics of Equity Covariance," Manuscript, UCSD.

Taylor, S. J., 1986, *Modeling Financial Time Series*, John Wiley and Sons Ltd.

Wooldridge, J, 1991, "On the application of robust, regression based diagnostics to models of conditional means and conditional variances", *Journal of Econometrics*, Vol. 47, pp 5-46.

Wooldridge, J., 1990, "A unified approach to robust, regression-based specification tests," *Econometric Theory*, Vol. 6, pp. 17-43.

Wu, G., 2001, "The Determinants of Asymmetric Volatility," *Review of Financial Studies*, Vol. 14, pp. 837-59.

Zakoian, J., 1994, "Threshold heteroskedastic models," *Journal of Economic Dynamics and Control*, Vol. 18, pp. 931-55.

Table 1

Equity Indices

	Mean	Min	Max	
	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	Min	Max	
	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

Between Bond & Equity Indices

	Mean	Min	Max	
	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

Table 1: Summary Statistics for the 21 Equity Index returns and 13 Bond Index returns correlations, grouped by region. The numbers are the average correlation between the appropriate groups, i.e. in the last section, the upper left element is the average correlation between Australasian equity returns and Australasian bond returns.

Table 2a

	Austria	Belgium	Canada	Denmark	France	Germany	H. K.	Ireland	Italy	Japan	Mexico	Neth'l	N. Z.	Norway	Singapore	Spain	Sweden	Switz'l	U. K.	U. S.
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
H. K.								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
Neth'l													0.375	0.573	0.436	0.612	0.600	0.729	0.663	0.522
N. Z.														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
Switz'l																			0.585	0.398
U. K.																				0.495

Table 2a: Unconditional correlation of returns of the equity markets in this study.

Table 2b

	Austria	Belgium	Canada	Denmark	France	Germany	Ireland	Japan	Neth'l	Sweden	Switz'l	U. K.	U. S.
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
H. K.	-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
Neth'l	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
N. Z.	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
Switz'l	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
U. K.	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
U. S.	-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

Table 2b: Unconditional correlation of returns across the equity (down) and bond markets (across). Red numbers indicate negative correlation. 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 2c

	Belgium	Canada	Denmark	France	Germany	Ireland	Japan	Neth'l	Sweden	Switz'l	U. K.	U. S.
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
Neth'l									0.667	0.861	0.657	0.234
Sweden										0.553	0.566	0.173
Switz'l											0.589	0.126
U. K.												0.249

Table 2c: Unconditional correlation of returns across the bond returns. Red numbers indicate negative correlation.

Table 3

	Overall	Intra-stock	Intra-bond	Interstock Bond
Significant at 10%	0.146	0.291	0.077	0.055
Significant at 20%	0.292	0.552	0.154	0.132

	Stocks Only	Significant at 20%		
		Australasia	Europe	North America
	Australasia	0.500		
	Europe	0.323	0.333	
	North America	0.133	0.180	0.000

	Bonds only	Significant at 20%		
		Australasia	Europe	North America
	Australasia	-		
	Europe	0.000	0.133	
	North America	0.000	0.000	0.000

	Across Stocks - Bonds	Significant at 20%	Stocks	
		Australasia	Europe	North America
	Australasia	0.000	0.000	0.000
Bonds	Europe	0.020	0.069	0.033
	North America	0.100	0.000	0.500

Table 3: Summary Statistics for conditional partial correlation. The numbers represent the percentage of the series rejecting the null that the conditional partial correlation is the same after joint bad news(two negative returns) as it as after joint good news(two positive returns). Except where explicitly indicated, all tests were at the 10% level.

Table 4

	Mean§	Standard Dev.§	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
United Kingdom Stocks	10.99	17.59	-1.07	15.24	-1.06	12.01
United States 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
United Kingdom Bonds	8.74	10.97	-0.03	4.54	-0.08	3.96
United States Bonds	6.94	4.55	0.43	8.72	0.08	5.18

Table 4: Summary Statistics for the 21 Equity Index returns and 13 Bond Index returns. The standardized skewness and standardized kurtosis are the skewness and kurtosis of the returns standardized by their estimated standard deviation. (§ denotes Annualized Percent, * denotes standardized residuals insignificantly different from a normal distribution at 5%, ** at 1%)

Table 5

Asset	Model Selected	*w* §	*a*	*g* or *d*	*b*
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
United States Stocks	ZARCH	0.0084	0.0369	0.0841	0.9098
United Kingdom 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
United Kingdom Bonds	GARCH	0.0001	0.0242		0.9706
United States Bonds	GJR-GARCH	0.0008	0.0400	0.1475	0.7184

Table 5: Model selected 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. §Intercept parameters were actually calculate on 10 times the returns to facilitate working with extremely small numbers.

Table 6

	Symmetric Model		Asymmetric Model		
	a_i^2	b_i^2	a_i^2	b_i^2	g_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
United Kingdom Stocks	0.0079	0.9484	0.0066	0.0064	0.9549
United States 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
United Kingdom Bonds	0.0091	0.9689	0.0058	0.0041	0.9716
United States Bonds	0.0096	0.9277	0.0058	0.0027	0.9361
Scalar Model	0.01010	0.94258	0.00817	0.00653	0.94816

Table 6: Parameter estimates for the symmetric and asymmetric models in the paper. * indicates insignificant at the 5% level.

Table 6a

Scalar DCC	-25722.1	Scalar Asym. DCC	-25704.7
Scalar DCC w/ mean break	-24816.2	Scalar Asym. DCC w/ mean break	-24809.2
Scalar DCC w/ mean and dynamics breaks	-24789.2	Scalar Asym. DCC w/ mean and dynamics breaks	-24781.6
Diagonal DCC	-25564.5	Diagonal Asym. DCC	-25485.1
Diagonal DCC w/ mean break	-24572.5	Diagonal Asym. DCC w/ mean break	-24487.5
Diagonal DCC w/ mean and dynamics breaks	-24483.3	Diagonal Asym. DCC w/ mean and dynamics breaks	-24398.3

Table 6a: Log-likelihood values for the 12 models estimated in the paper. 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.

Table 7

	Overall	Stocks	Bonds
x_1	0.0242	0.0112	0.0452
x_2	0.0606	0.0224	0.1222
x_3	0.0631	0.0322	0.1131
X_4	0.0779	0.0518	0.1199

	Equity	Bond
Equity	0.0306	0.0399
Bond	0.0275	0.1374

Table 7: Rejection rates for the robust conditional moment test for the estimated volatilities. The top pane is the percent of the tests rejecting for each of the factors x_i, i=1,2,3,4. The bottom pane is the rejection rate of the series of a given type in the left column with moments of the series of the type listed across.

Table 8

overall	0.0533
x5	0.0875
x6	0.0457
x7	0.0121
x8	0.0598
x9	0.0367
x10	0.0811
x11	0.0748
x12	0.0287

Table 8: Rejection rates for the robust conditional moment test for the estimated correlations. The statistics represent the percent of the tests rejecting for each of the factors x_i, i=6,7,…,12.

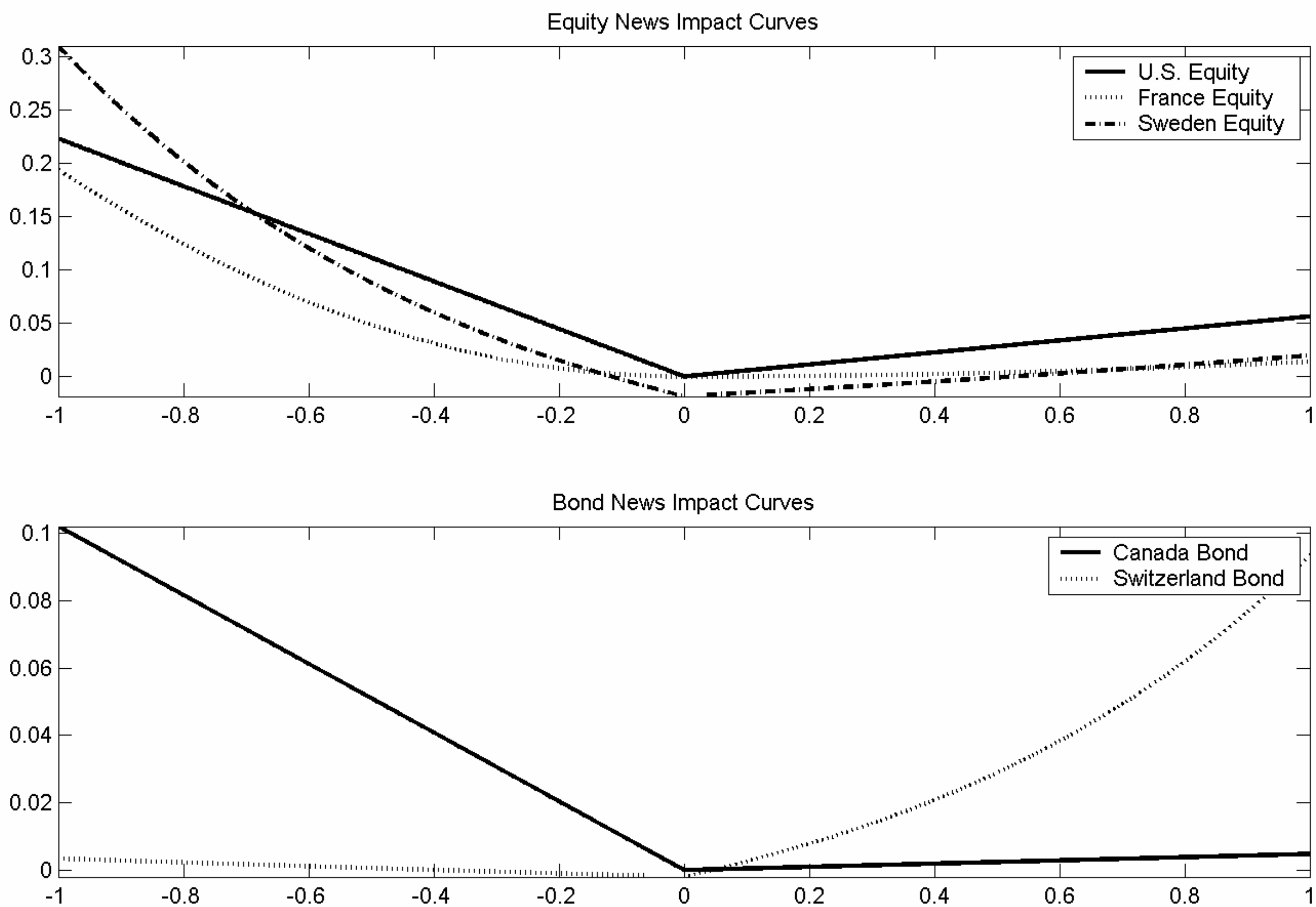

Figure 1: Typical volatility news impact curves for equities and bonds. The volatility dynamics can take on a wide range of forms, including decreasing for positive shocks in the case of an EGARCH model (German Equities), or showing no increase subsequent to a positive shock in the case of Canadian bond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

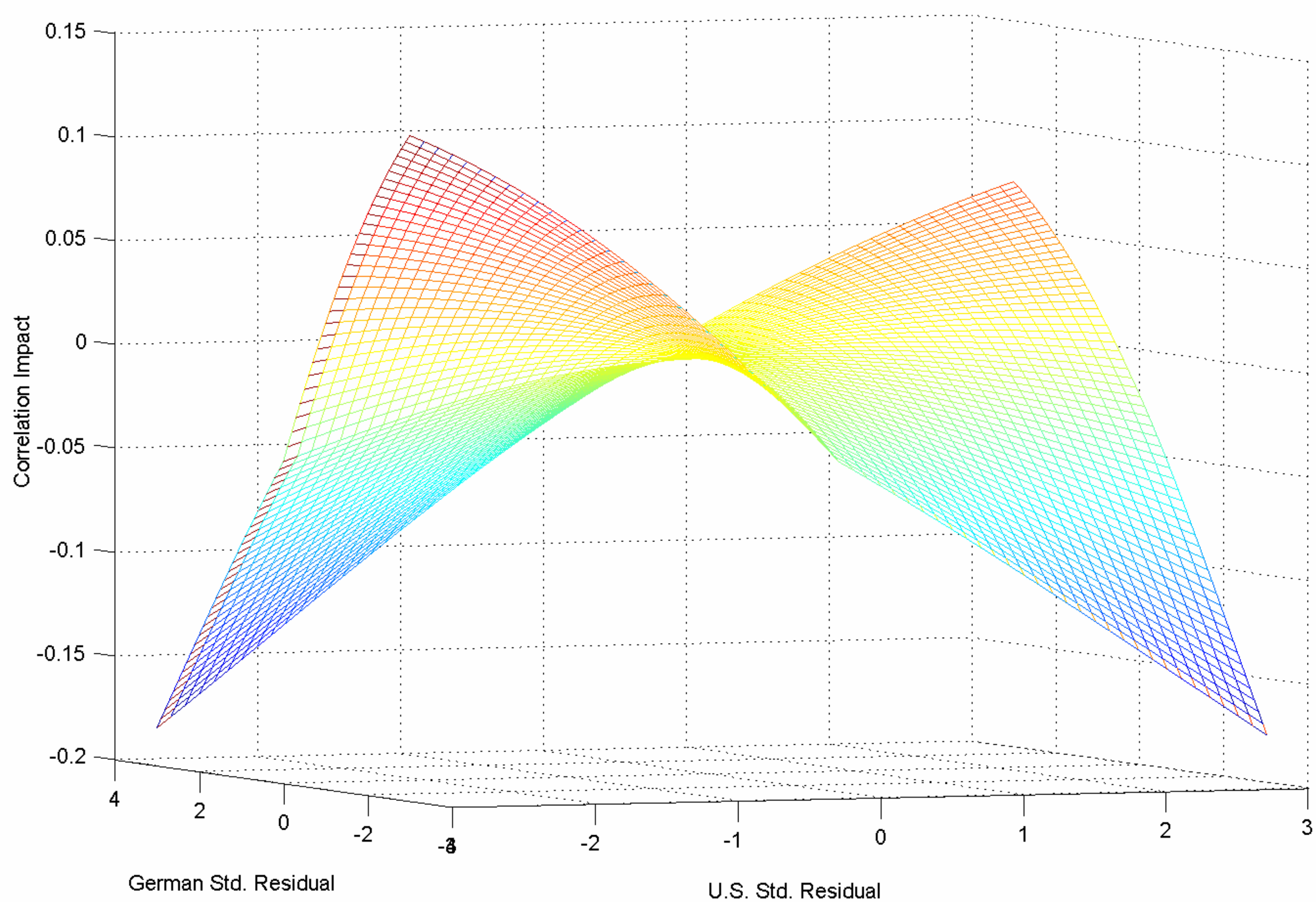

Figure 2: Correlation news impact surface for German and US equity returns. There is significant asymmetry in the negative-negative quadrant, evidenced by the dark red coloring,

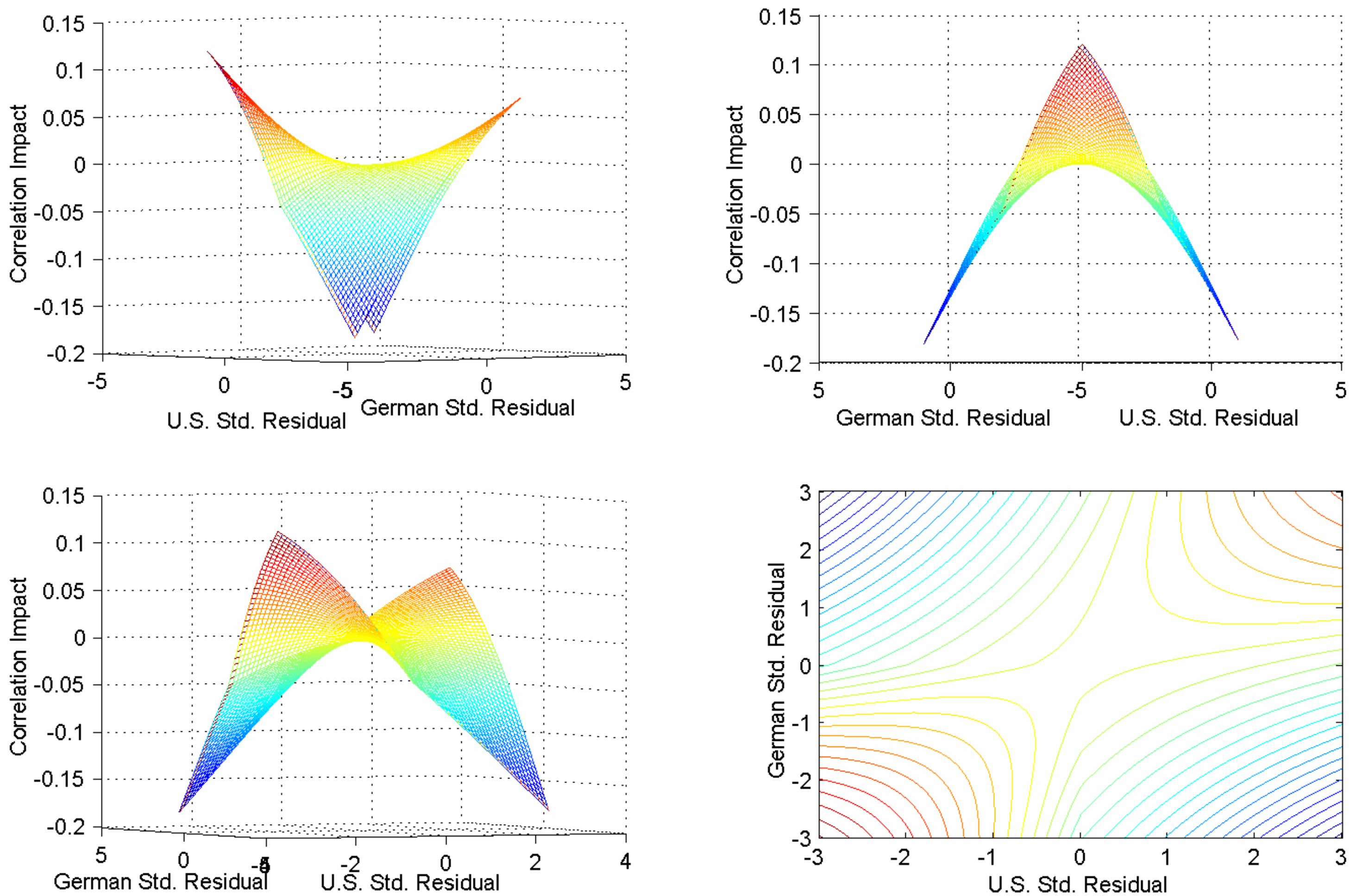

Figure 2b: Four looks at the correlation news impact surface for German and US equity returns. The asymmetry is apparent in the upper left and the lower right contour plot. There is little asymmetry between +- and -+ standardized returns.

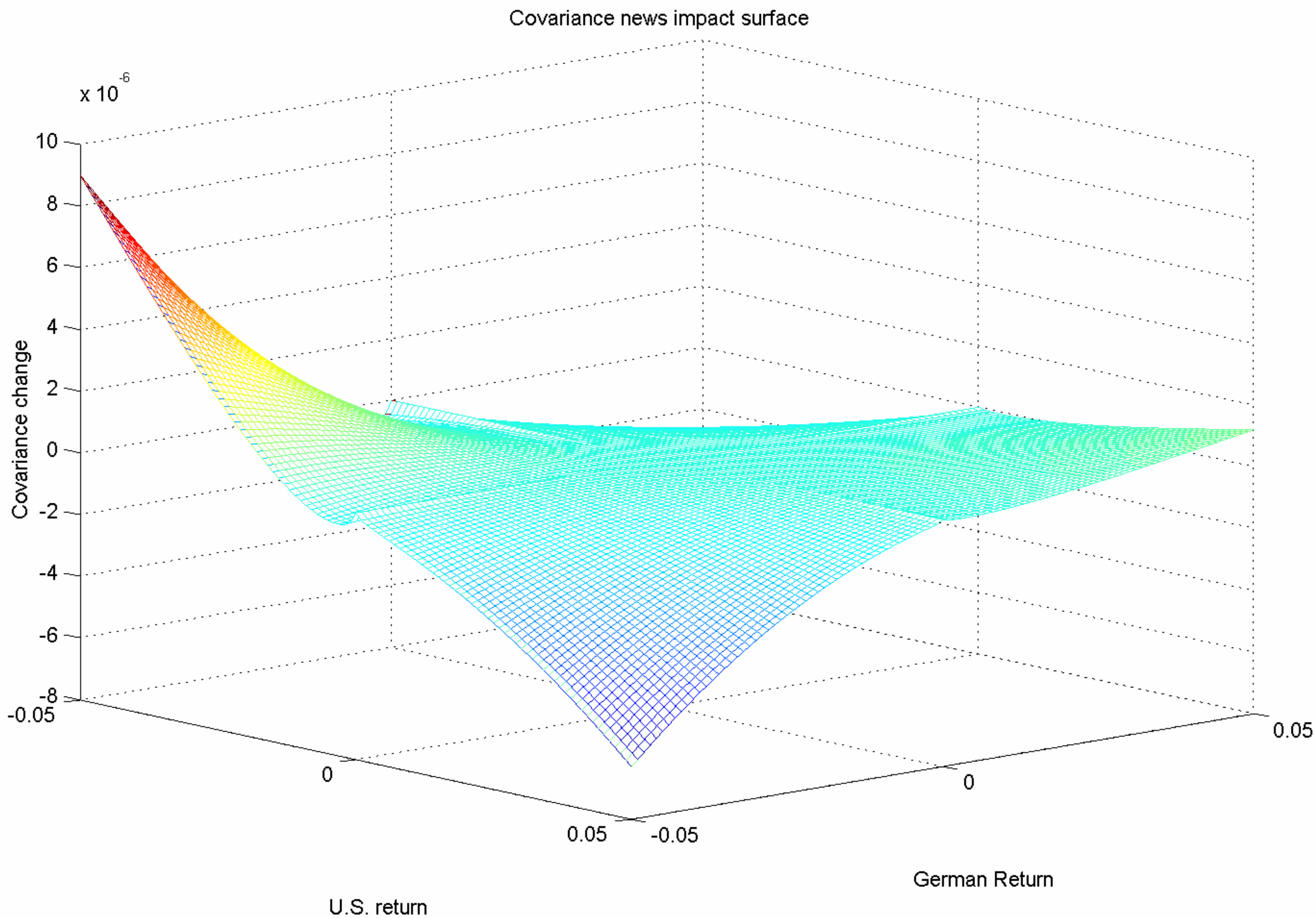

Figure 3: News impact surface for covariance. Although the news impact surface is increasing in both the ++ and the – quadrants, the correlation combined with covariance results in a steep increase in the – quadrant and a near flat response in the ++ quadrant, as well as asymmetries between the +- and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

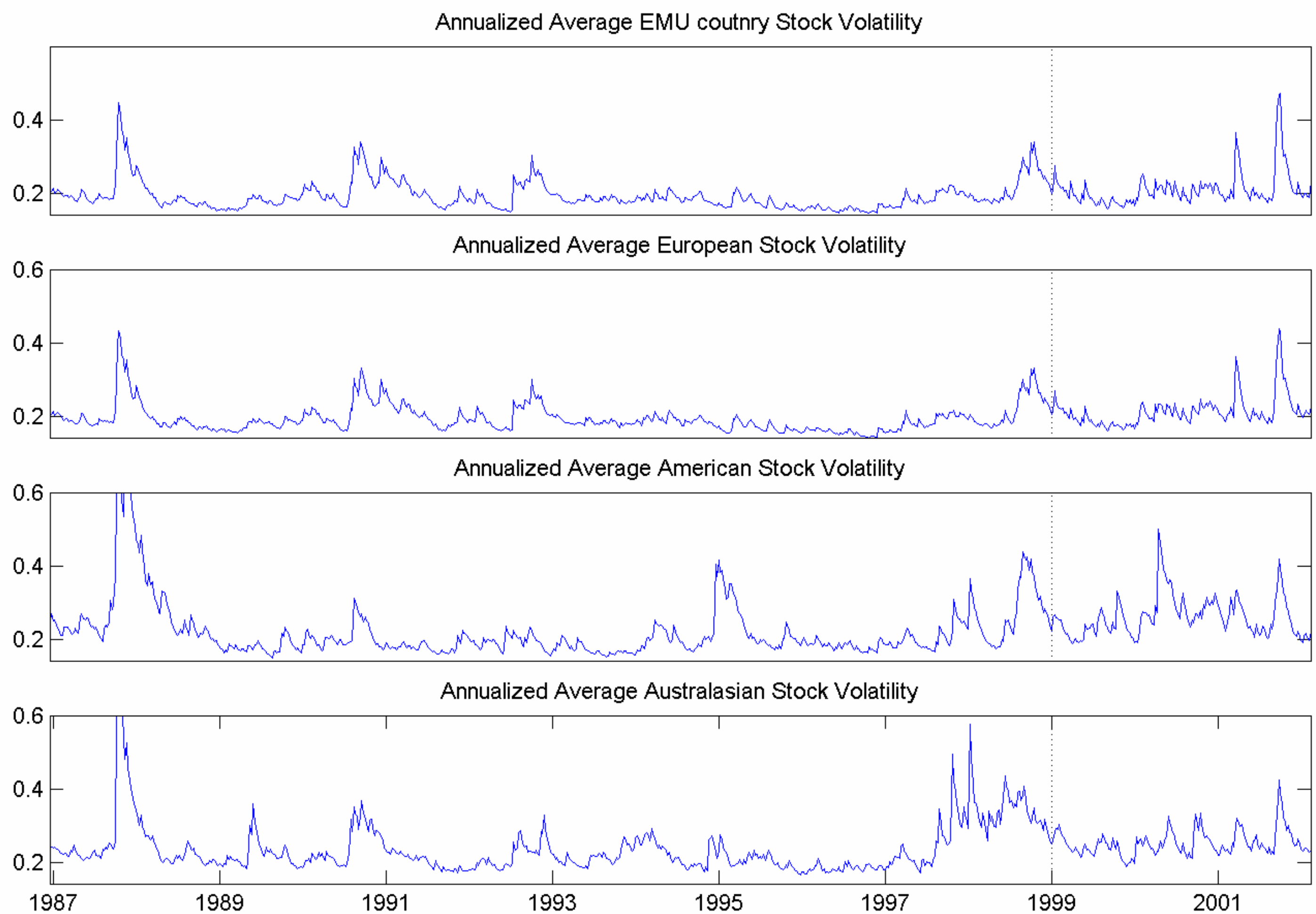

Figure 4: Plots of the annualized conditional equity volatility for four groups of countries. There appear to be strong linkages in equity volatility across regions, evidenced by October '87, Mid 1990-91, and 1997-98, and late 2001.

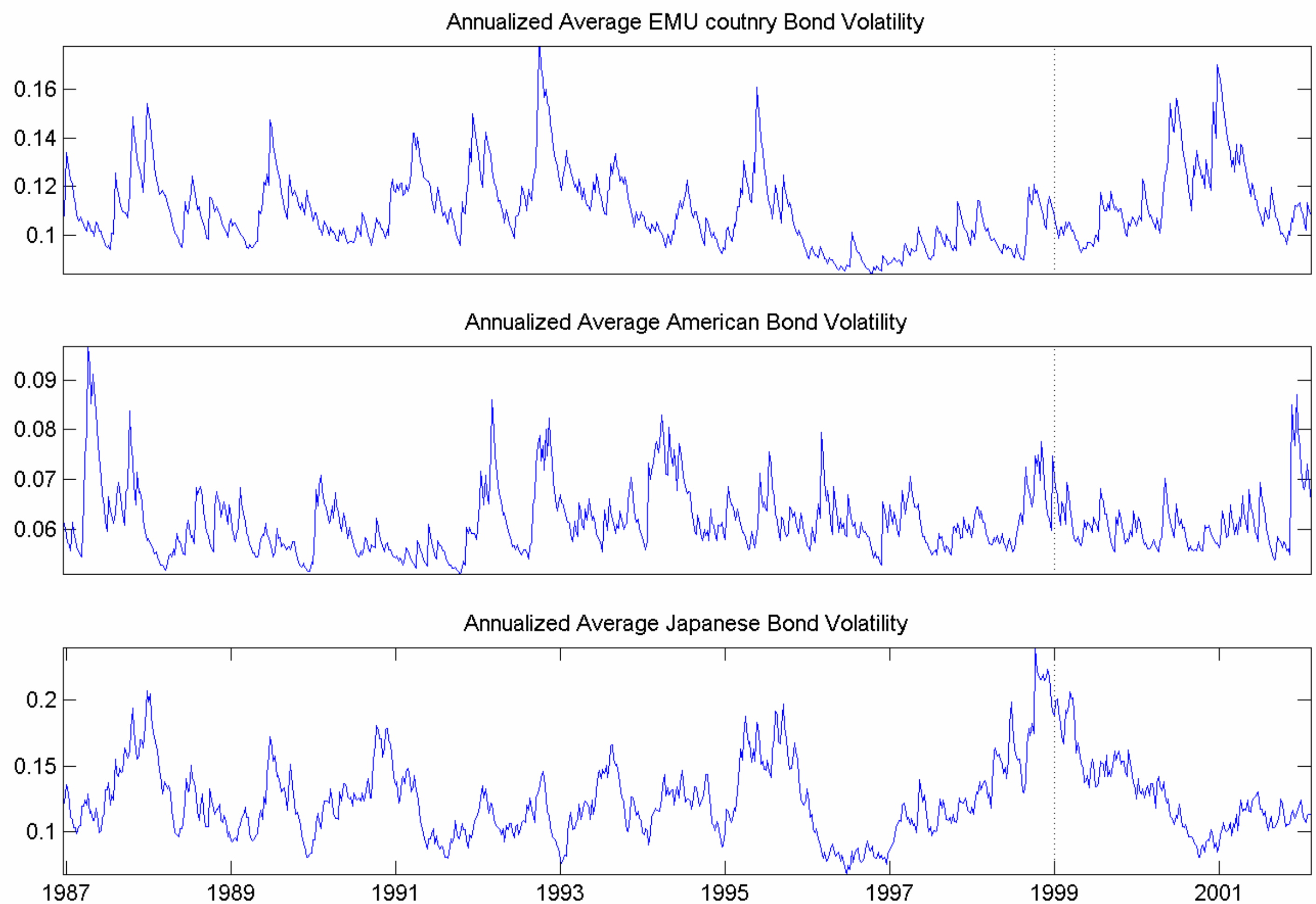

Figure 5: Plots of the annualized conditional bond return volatility for the EMU countries, the U.S. and Japan. Unlike equities, bond markets do not exhibit strong linkages in volatility.

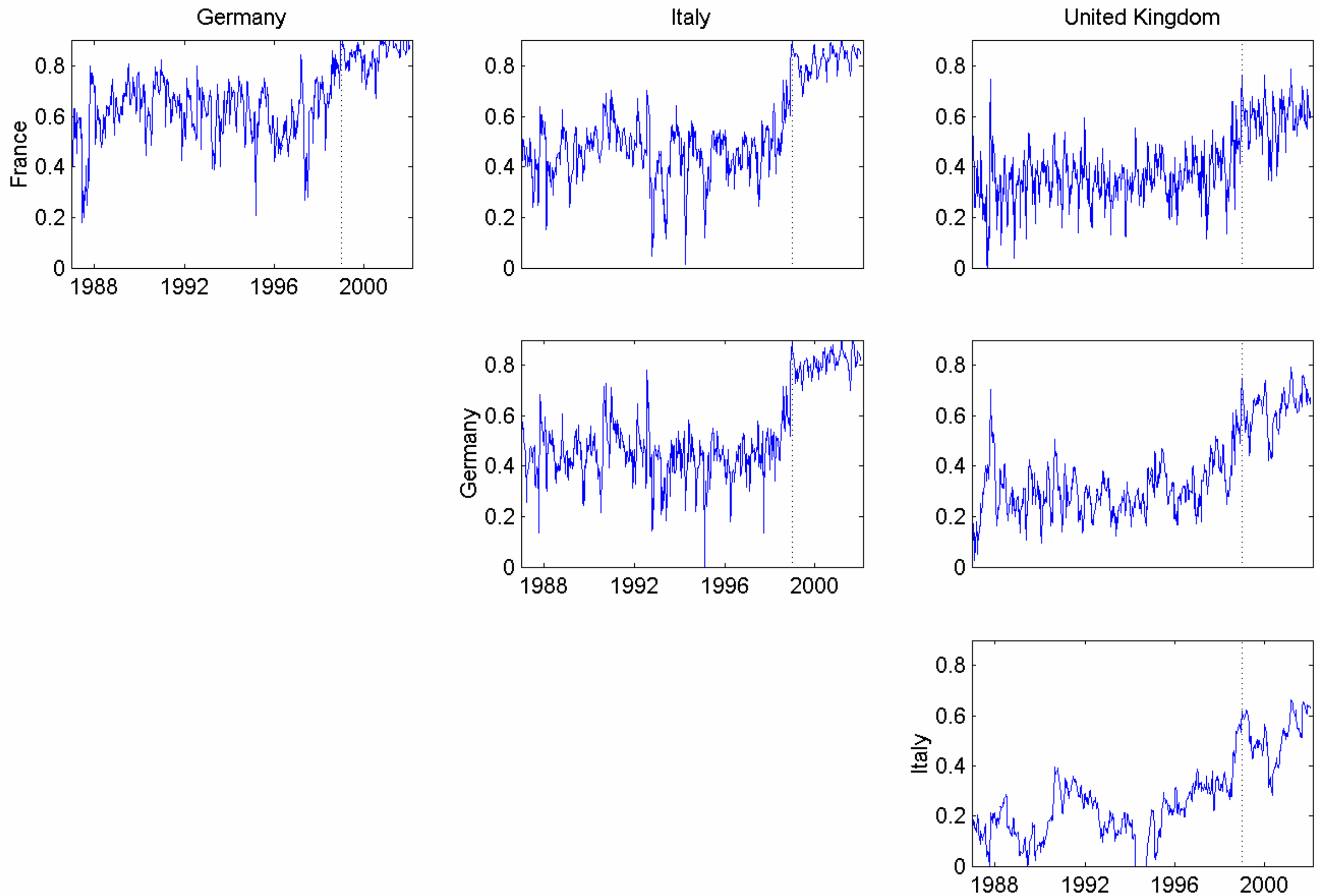

Figure 6: Plot of the conditional correlation for four European countries, three of which are in the EMU. There is a strong increase in correlation on January 1, 1999 for all four countries, and the increase was larger within the EMU countries than between Great Britain and the 3 EMU countries.

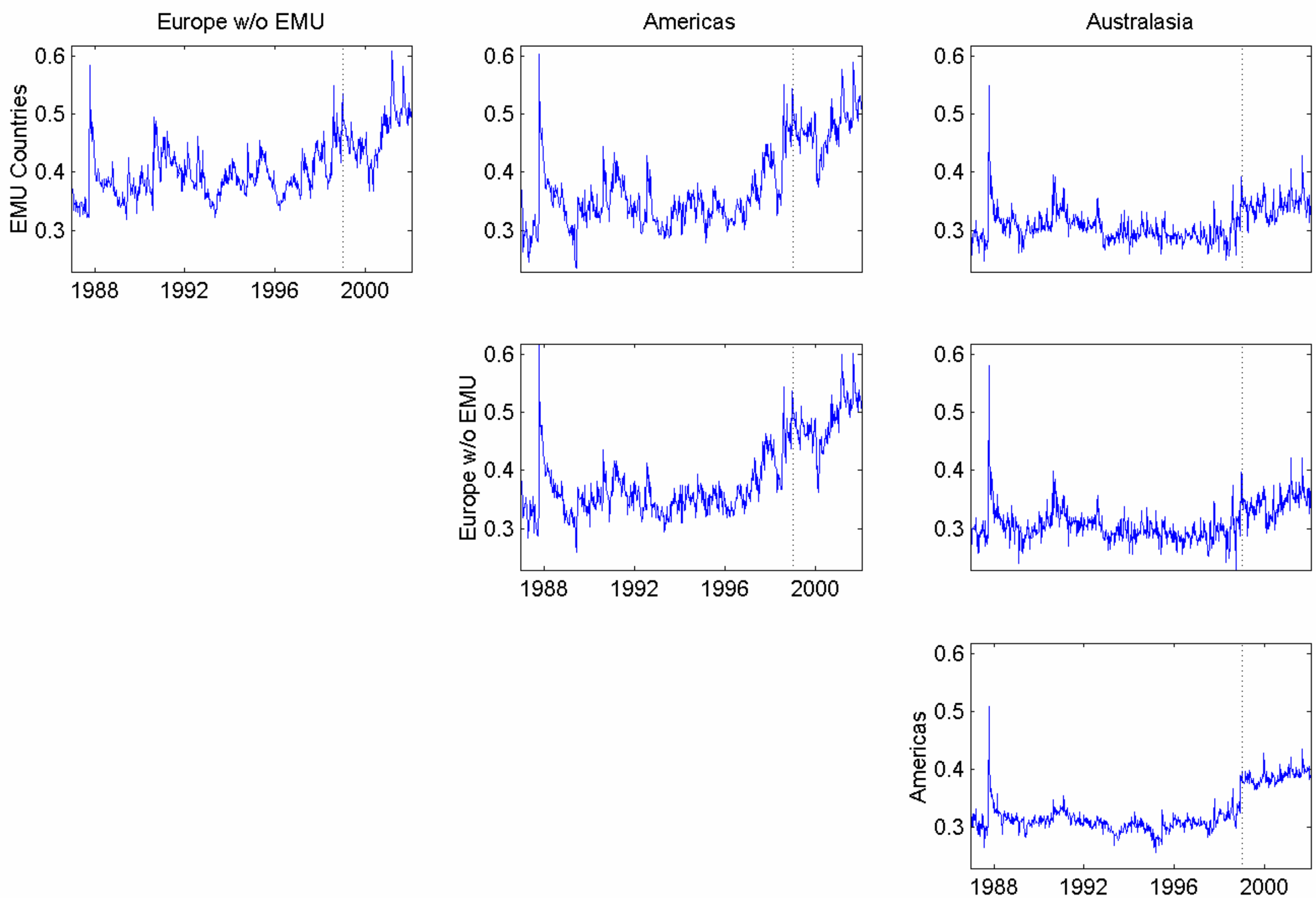

Figure 7: Plot of the average correlation between equity in the EMU countries, the remainder of Europe, the Americas, and Australasia. With the exception of 1987, simultaneous decreases in correlation appear to be more widespread then increases.

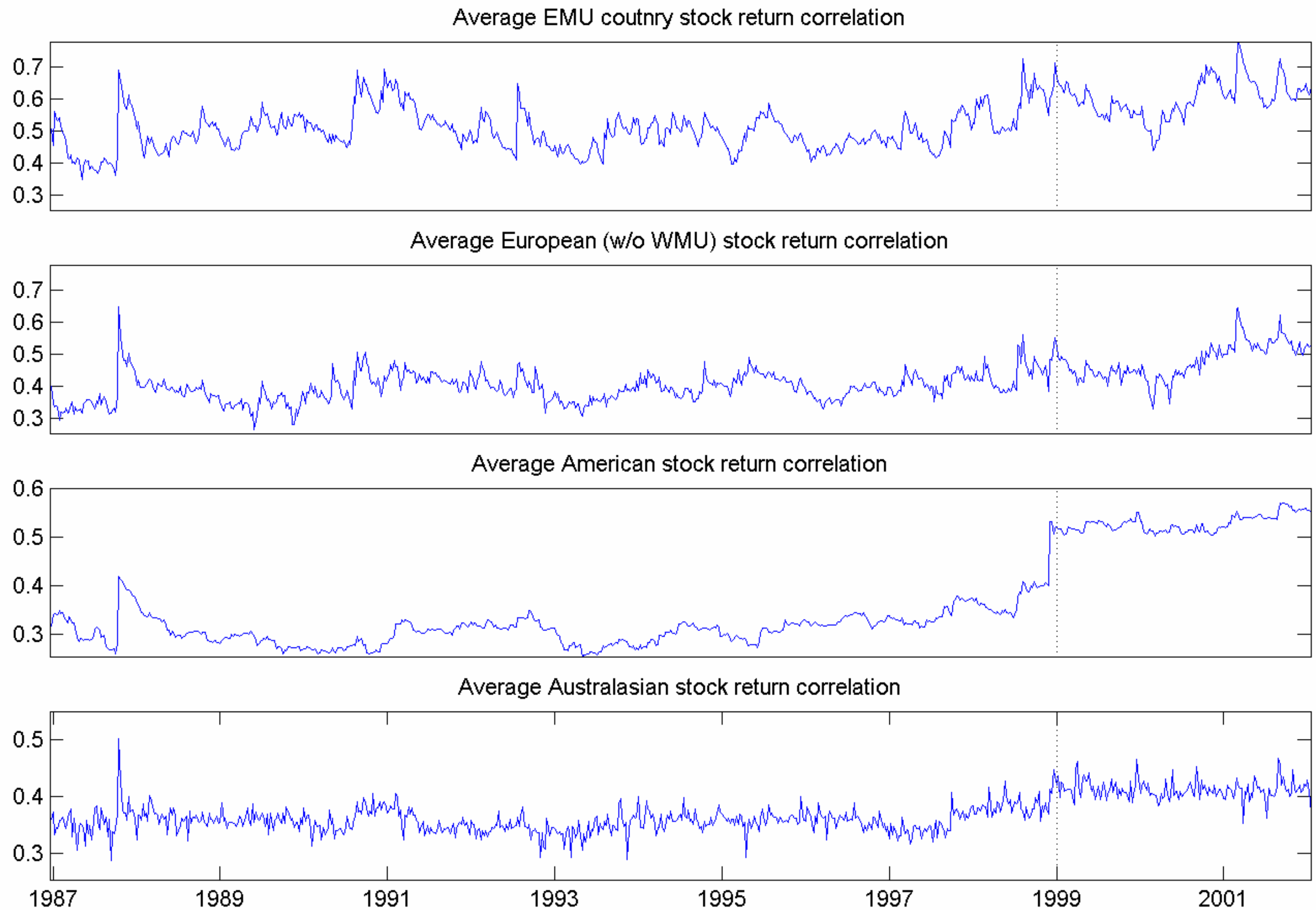

Figure 8: Plot of the average equity correlation with four groups of countries. Both the EMU and European equity return correlation appear to have had an increase over the past 5 years, most likely due to the final realization of the EMU. The correlation of equity returns of the Americas have also dramatically increased since 1997.

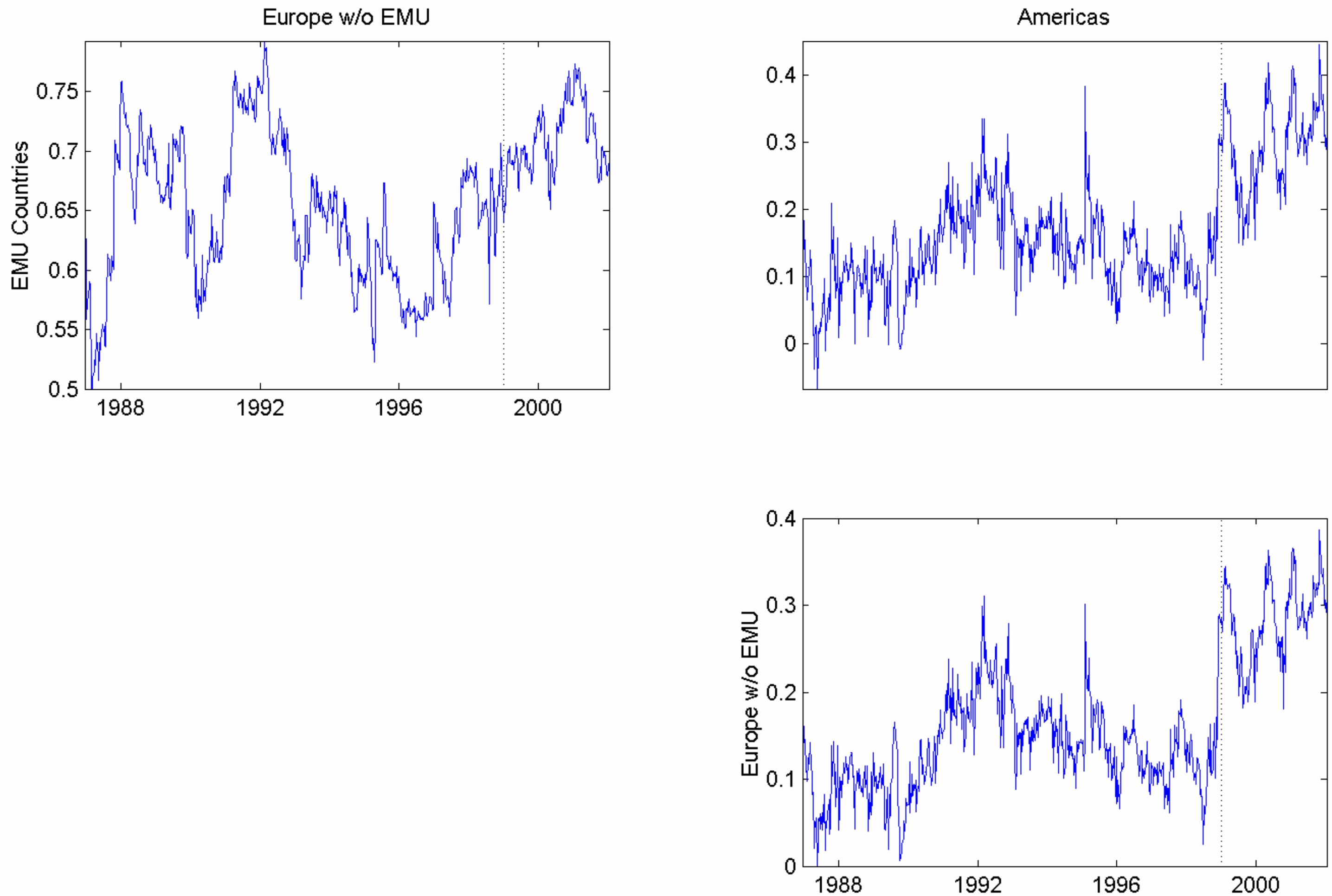

Figure 9: Plot of bond return correlation between the EMU, the rest of Europe, and the U.S. The finalization of the EMU seems to have increased correlation between the EMU countries and the U.S., while correlations between the U.S and the non-EMU European countries appear to be similar to before the exchange rate fixing.

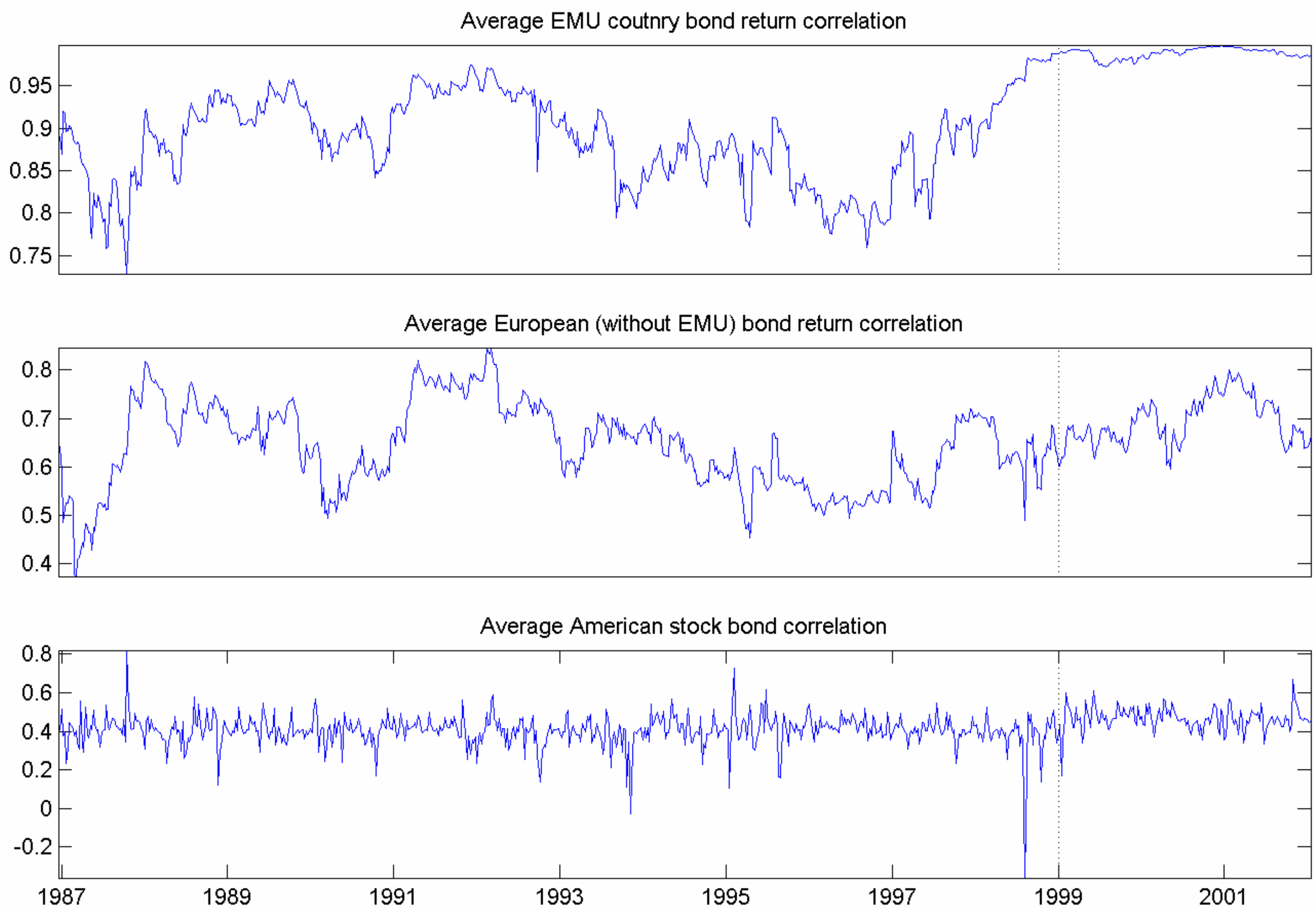

Figure 10: Average bond correlation for three groups of countries. The bond return correlation within the EMU is effectively one since the fixed exchange rate regime began, yet over all bond market correlation within Europe has not increased nearly as much, indicating a decrease in correlation between the EMU countries and the non-EMU European countries bond returns. The bond return correlation in the Americas has also increased sharply in the last 4 years.

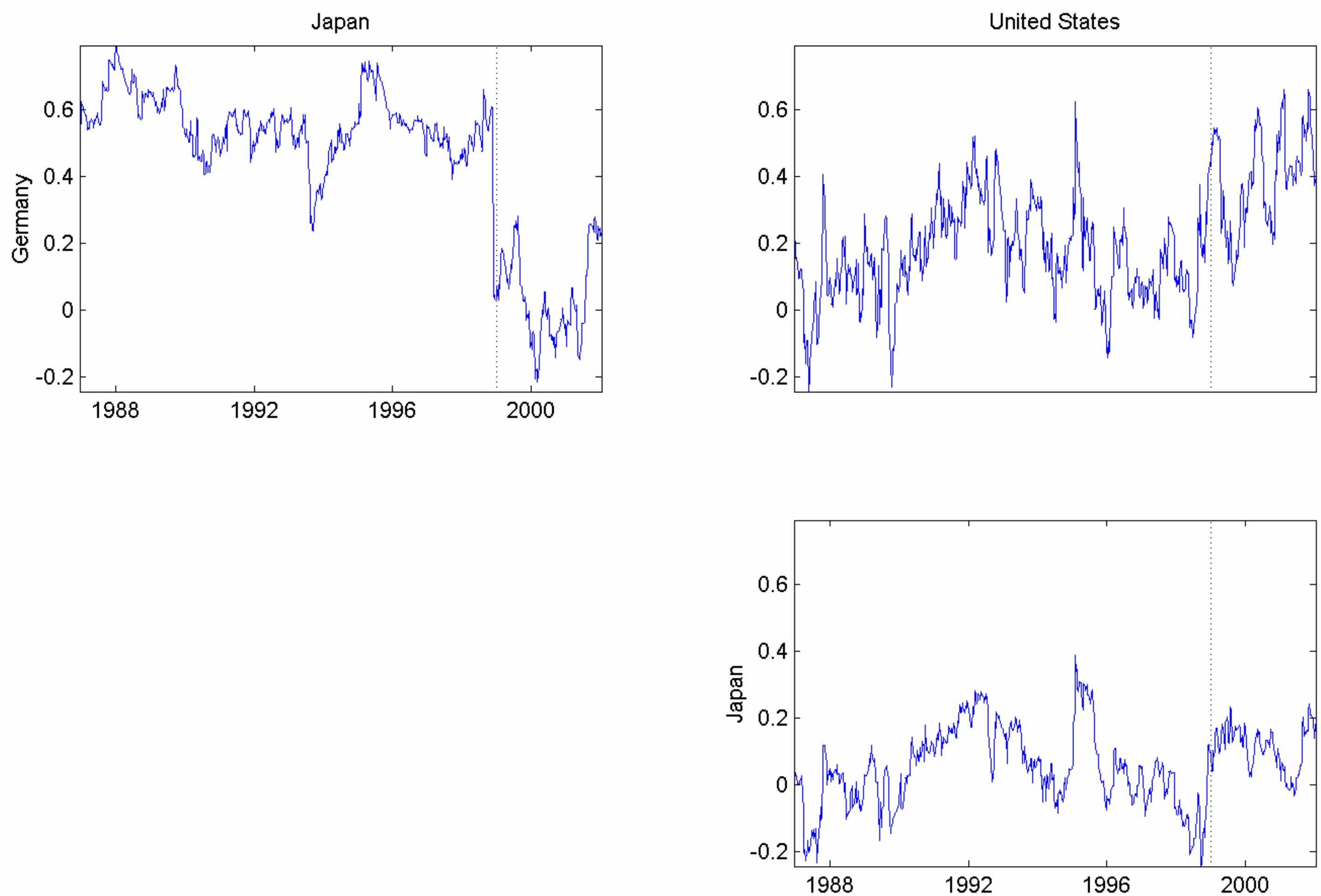

Figure 11: Bond return correlation between three leading providers of government bonds, Germany, Japan, and the U.S. The correlation between Japanese bond returns and German bond returns dropped dramatically at the introduction of the Euro, while correlation between German and U.S. bond returns has increased although with increasing noise.

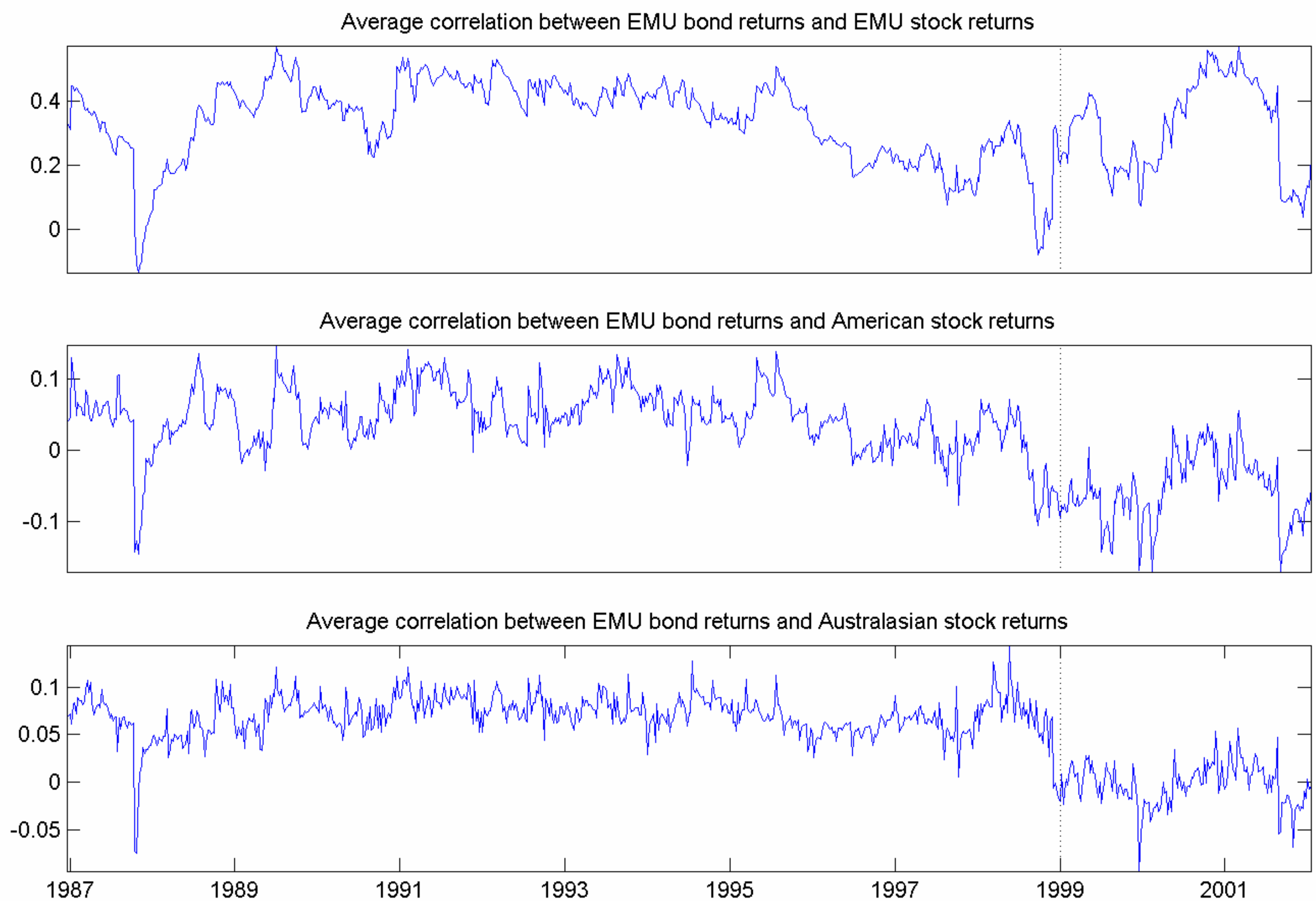

Figure 12: Plot of the average correlations between EMU bond returns and equity returns from the three main regions. There appear to be very strong linkages in the three series, as evidenced by October 1987, 1997-98, and late 2001.

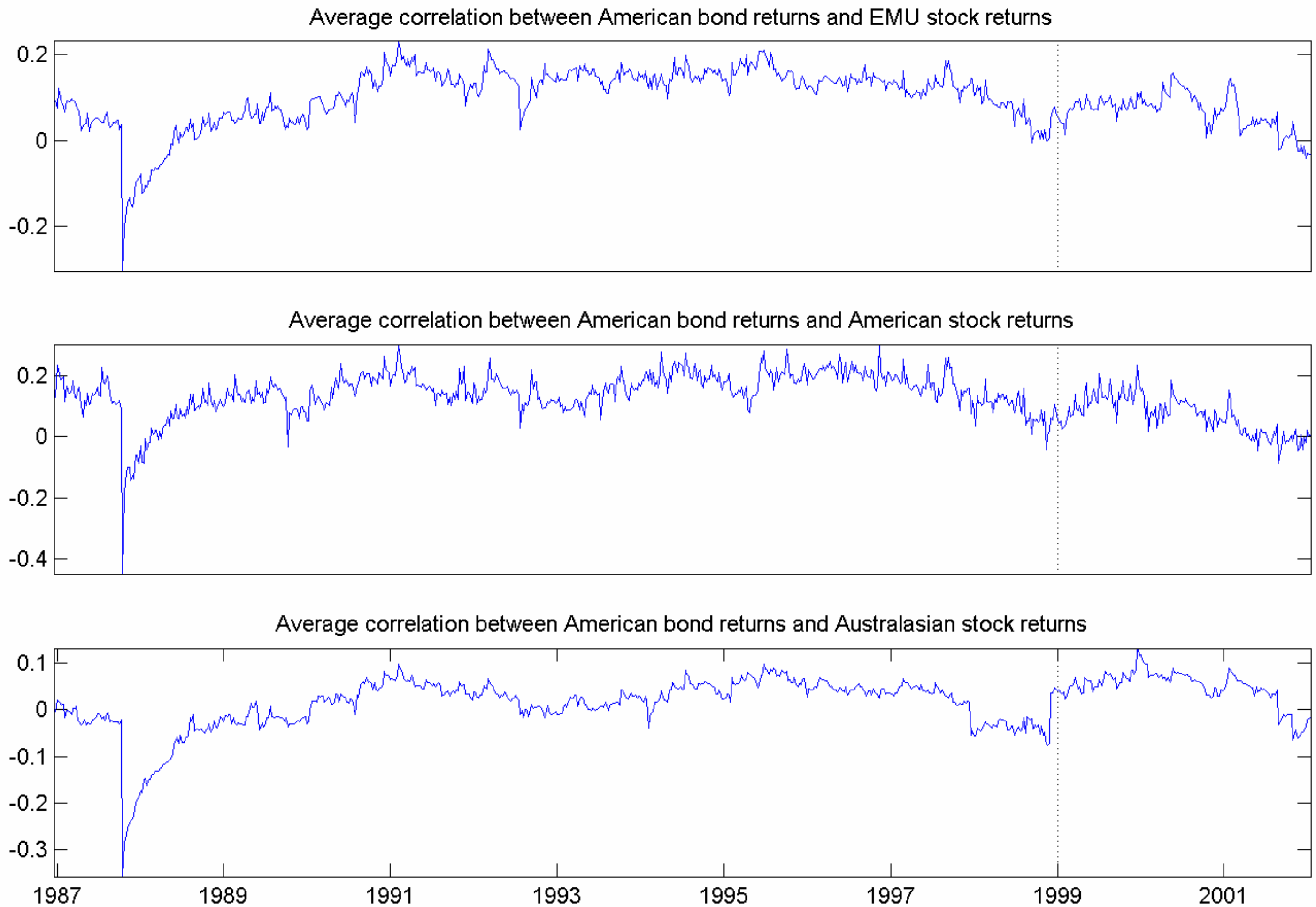

Figure 13: Plot of the average correlations between American bond returns and equity returns from the three main regions. There also appear to be very strong linkages in the three series, as evidenced by October 1987 and very similar shapes (although they have different unconditional levels).