Financial Co-Movement and Correlation: Evidence from 33 International Stock Market Indices

Twm Evans
School of Business & Economics
University of Wales, Swansea

&

David G McMillan
School of Management
University of St Andrews

December 2006

Abstract

The analysis of financial market co-movement is an important issue for both policy makers and portfolio managers, for example, in terms of policy co-ordination and portfolio diversification. This paper presents evidence based on a data set of 33 daily international stock market indices. Initially using established cointegration and multivariate GARCH frameworks we report results that suggest correlations with the US have not in general exhibited an upward trend. The main exception to this is the G7 economies, although even here the correlations declined over the last two years of the sample. On a regional basis stronger evidence of rising correlations is reported, although again this evidence is not ubiquitous. Further, we then implement the recently developed non-parametric, model-free, realised variance methodology to generate monthly correlation coefficients. This method overcomes deficiencies in both the cointegration and GARCH methods. The results found at the daily level are largely confirmed by the realised correlations. Finally, we use the realised correlation coefficients to form international portfolios and compare the level of risk to that of an equally weighted portfolio. Results suggest the portfolios weighted according to the realised correlations exhibit diversification benefits over the equally weighted portfolios. Our results thus suggest that there remains room for portfolio managers to obtain diversification benefits, while policy makers may need to take in account possible adjustment costs of co-ordinated action.

Keywords: Cointegration, Correlation, Multivariate GARCH, Realised Volatility
JEL: G12

Address for Correspondence: Dr David McMillan, School of Management,
University of St Andrews, The Gateway, North Haugh, St Andrews, KY16 9SS, UK.
Tel: +44 (0) 1334 462800. Fax: +44 (0) 1334 462812
e-mail: dgm6@st-andrews.ac.uk

I. Introduction.

Analysis of financial market co-movement and correlation is an important issue for both policy makers and market participants, such as portfolio managers. That is, for policy makers, common movement and convergence would support transition in local currency areas (such as the Euro) without significant stock market adjustment caused by any business cycle adjustment. Moreover, such convergence may imply potential efficiency gains from stock market merger activity. Furthermore, financial convergence may lead to greater financial stability and policy coordination across regions. With regard to portfolio managers, increased correlations and co-movement between international stock markets would imply reductions in the benefits of portfolio diversification, such that portfolio managers would need to actively adjust their portfolios in search of assets with lower correlations.

The general view within the literature is that correlations between assets are time-varying, with evidence in particular noting increases in correlations across international stock markets at times of stress (see, for example, King and Wadhwani, 1990; Karolyi and Stulz, 1996; Forbes and Rigobon 2002) and at different stages of the business cycle (Erb et al, 1994; Longin and Solnik, 1995). However, it is unclear as to whether correlations amongst equity markets have trended upwards over time, although at present, the balance of evidence suggests that they have (see, for example, Roll, 1989; King et al, 1994; Longin and Solnik, 1995; Rangvid, 2001; Goetzmann et al 2001).

The extant literature has largely conducted investigations of international equity market correlations and convergence along two lines. The first line of enquiry examines whether there is any evidence of cointegration amongst international stock indices (see, for example, Taylor and Tonks, 1989; Kasa, 1992; Corhay et al, 1993;

Aggarwal and Kyaw, 2005; Fraser and Oyefeso, 2005). The belief being that should stock markets exhibit cointegration and therefore follow the same long-run time path (or stochastic trend) then any gains from diversification across an international portfolio will be confined to short-run horizons when markets temporarily diverge from their long-run path. On balance, evidence from the papers cited above lends support to the belief that co-movement does exist in the long-run behaviour of series.

The second line of enquiry attempts to directly model time-variation within correlation coefficients between series through a multivariate extension of the GARCH model (see, for example, Ragunathan and Mitchell, 1997; Berben and Jansen, 2005; Kim et al, 2005). One argument in favour of this approach is that cointegration analysis assumes a long-run stable equilibrium path, whereas the process of financial convergence (should it occur) is a dynamic process that exhibits strong time-variation. Again, evidence with regard to the time-varying nature of correlations is mixed, with, for example, Longin and Solnik (1995) arguing in favour of increased correlations amongst the US, UK, France, Japan and Switzerland, and Kim et al (2005) arguing in favour of integration within EMU countries, while King et al (1994) and Ragunathan and Mitchell (1997) argue that there has been little increase in correlations across international stock markets

However, both of these lines of enquiry suffer from potential drawbacks, first, as noted cointegration analysis is not able to capture the fluid nature of financial integration but instead looks for commonality over a fixed time frame. Furthermore, cointegration results only impart economic significance when examined over sufficiently long time horizons, such that increasing the number of observations by using higher-frequency data over shorter time frames does not necessarily produce meaningful results. Second, the GARCH approach is beset by two problems, first the

need to ensure tractable estimation, for example, a fully specified bivariate-GARCH(1,1) model has 21 parameters. As such, a variety of alternate methods exist in order to conduct such estimation. This is further complicated by the existence of several GARCH specification designed to capture different aspects of the data, for example, asymmetric and long-memory GARCH models. The net effect of this is that no single specification dominates and indeed differing results may be obtained from different GARCH specifications. Thus, in addition to the methods noted above, we also compute realised correlations based upon the recently devised realised variance methodology and which is regarded as free from measurement error and provides a model-free nonparametric framework in which to examine time-variation in volatilities.

The aim of this paper is to reconsider the temporal nature of international stock market correlation in the light of the three methodologies noted above utilising a large data set of international stock market indices. In Section II we re-consider evidence of cointegration between both major industrial economies and regional economies. The belief is that increasing integration between equity markets of the major economies has led to investors to seek diversification benefits in the more emerging economies. In Section III we consider bivariate GARCH models to examine for any trending behaviour in the dynamics of correlations between countries. Whilst these previous two sections consider daily data, Section IV models correlations at the monthly frequency but utilising the information content at the daily level through the construction of realised correlations, for which this study represents one of the first to apply the realised volatility methodology to the analysis of portfolio correlations. Furthermore, we use the estimated time-varying realised correlation coefficients to construct international portfolios and compare the risk within these

portfolios to equally-weighted constructed portfolios. Section V summarises and concludes.

II. Data and Cointegration Results.

Data from thirty-three international stock market indices was collected over the period 3/1/1994 – 27/4/2005, resulting in 2950 observations. This data represents a good cross-section of data from developed, emerging and developing economies, and for which summary statistics for returns (differenced log values) and unit root tests for the log-levels are presented in Table 1. The data in this table is grouped according to G7 membership and region, and these groupings are used in the cointegration tests. These summary statistics reveal the usual characteristics of daily equity returns, that is, a small mean value and a larger standard deviation. Furthermore, evidence of non-normality and in particular excess kurtosis is evident, and which is more pronounced for the economies that exhibit a lower level of development. Finally, ADF tests support the belief of a unit root in the levels of the data.

In order to test for cointegration we employ the well-known technique of Johansen (1996), and thus only briefly state it here. To test for cointegration we use the *p*-dimensional vector autoregressive process of *k*th order:

(1) $$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-k} + \varepsilon_t$$

where Δ is the first-difference operator, Y_t is a (p x 1) random vector of time series variable integrated of order one or less, μ is a (p x 1) vector of constants, Γ_i are (p x p) matrices of parameters, ε_t is a sequence of zero-mean p-dimensional white noise vectors, and Π is a (p x p) matrix of parameters the rank of which contains information about long-run relationships among the variables. As is well known, the VECM expressed in equation (1) reduces to an orthodox vector autoregressive (VAR)

model in first-differences if the rank (r) of Π is zero, whilst if Π has full rank, $r = p$, all elements in Y_t are stationary. More interestingly, $0<r<p$ suggests the existence of r cointegrating vectors, such that there exist (p x r) matrices α and β each of rank r and such that $\Pi=\alpha\beta'$, where the columns of the matrix α are adjustment (or loading) factors and the rows of the matrix β are the cointegrating vectors, with the property that $\beta' y_t$, is stationary even though Y_t may comprise of individually I(1) processes. Tests of the hypothesis that the number of cointegrating vectors is at most r ($r=1,\ldots,p$) are conducted using both the maximum-eigenvalue and trace test statistic for reduced rank in the context of the restrictions imposed by cointegration on the unrestricted VAR involving the series comprising Y_t.

The results of cointegration tests are reported in Table 2. The results presented here suggest for the G7, the two European and Others groupings there is a single cointegrating vector, that is just one long-run stationary relationship between the series. For the Asian group there are two cointegrating vectors, and one if Australia is excluded from the group. Thus, in the terminology of Stock and Watson (1988) there are six, eight, three, eight and two common stochastic trends for the G7, North Europe, South Europe, Asia and Other regions respectively. This suggests that although there is evidence of comovement amongst these international indices the evidence is not as strong as suggested by, for example, Kasa (1992) and Fraser and Oyefeso (2005) who argue for one common stochastic trend amongst the UK, US, Canada, Germany and Japan (Kasa) and UK, US and seven other European countries (Fraser and Oyefeso), but is similar to that of Corhay et al (1993) who report multiple common stochastic trends in the data for UK, France, Germany and the Netherlands. Our results support the view that whilst there is some evidence of convergence,

international stock markets are not fully integrated, even on a regional or market development basis.

As noted in the Introduction, one potential drawback of the cointegration methodology is that it does not allow for dynamic changes in the nature of the relationship between the series. Thus, we proceed to consideration of a model to account for such dynamics. However, before we consider estimates of the BV-GARCH models, to get an idea of any time-variation within the nature of the cointegrating relationships, we first consider rolling cointegration tests with a window of five-years. That is, we test for cointegration over the period 1/1/1994-31/12/1998 and then roll this window forward one period and re-conduct the cointegration test. The results of this procedure are plotted in Figure 1. What these results reveal is that the nature of the cointegrating relationship has not remained constant over the sample period. In particular, we can see for the G7 economies cointegration only appears in the latter part of the sample. For the regional groupings (North and South Europe and Asia) there is more evidence of cointegration throughout the sample period, although, even here, there are periods where cointegration is not supported, notably in 2002 for North Europe, late 1999/early 2000 for South Europe and the early 2000's for Asia. Unsurprisingly cointegration is rarely supported for the lesser-developed countries.

III. Bivariate GARCH Models.

Whilst the cointegration approach examines for long-run comovement, it can be argued that the process of integration is more fluid, with the degree of integration changing (increasing) over time, as such the cointegration approach may not capture this dynamic. Thus, we consider the bivariate GARCH approach in an attempt to directly model any change in correlations between international stock markets.

The formulation of bivariate GARCH model is given as:

(2) $$y_t = \mu_t + \varepsilon_t$$

where y_t is a 2×1 vector of random variables incorporating the returns on two stock indices. The 2×1 error vector ε_t is normally distributed with zero mean and conditional variance-covariance matrix given by $H=E(\varepsilon_t \ \varepsilon_t' \mid \psi_{t-1})$ where ψ_{t-1} is the information set up to time *t-1*. The general bivariate GARCH model is then given by:

(3) $$vech(H_t) = C + A_1 vech(\varepsilon_{t-1})^2 + B_1 vech(H_{t-1})$$

where C is a (3×1) parameter vector of constants, A_1, B_1 are (3×3) parameter matrices, and *vech* denotes the operator that stacks the lower portion of a matrix into a vector.

Several authors (for example, Engle and Kroner, 1995; Wahab, 1995) have discussed the difficulties that arise in determining the appropriate parameterisation of the conditional covariance matrix, for example a full bivariate (BV-) GARCH(1,1) model has twenty-one parameters to be estimated. A parsimonious parameterisation can be obtained by imposing a diagonal restriction on the multivariate parameter matrices, such that each variance and covariance element depends only upon its past values (Bollerslev, Engle and Wooldridge, 1988). However, in this specification it is non-trivial to ensure H is positive semi-definite. Thus, we employ the BEKK specification (Engle and Kroner, 1995) which guarantees positive semi-definiteness, hence our GARCH(1,1) model becomes:

(4) $$H_t = C'C + A_1'\varepsilon_{t-1}\varepsilon_{t-1}' A_1 + B_1' H_{t-1} B_1$$

where A, B, and C are (2×2) matrices, with A and B diagonal matrices with parameters A_1, A_2, B_1, and B_2, while matrix C is upper triangle with C_1, C_2 on the diagonal and C_3 the off-diagonal parameter. Finally, the time-varying correlation

statistic is computed as: $\rho_t = h_{12} / \sqrt{h_{1t}^2 \bullet h_{2t}^2}$, where h_{12} is the time-varying covariance term, and h_{1t}^2, h_{2t}^2 the time-varying volatilities of the two stock market returns respectively.

In order to examine time-variation in the correlations between international stock markets we first estimate our BV-GARCH(1,1) models for all series versus the US. In addition we also examine time-variation in the correlations between Japan and the Asian economies and Germany and the European economies. The results for the time-varying correlations with the US are reported in Table 3 (Figure 2 illustrates our results between the US and the remaining G7 countries), while the regional correlations with Germany and Japan are presented in Table 4.[i] Each of these tables presents the mean correlation over the full sample, the first 130 observations (equivalent to one-half of a trading year), the middle 130 observations and the final 130 observations. Finally, we also present the coefficient estimate of the correlation series regressed on a trend (and constant).

Examining the results first for the time-varying correlations with the US. The graphical results in Figure 2 reveal that there is a general upward trend in the correlation between the US and the G7 economies, and notably with Canada, France, Germany and Italy, but less so with Japan and the UK. Furthermore, the correlations appear to decline over the last two years. This finding is mirrored in the tabulated results where the estimated trend term is positive and relatively large for Germany and Italy. Further, the mean value of the correlation increases from the beginning of the sample to the middle of the sample for all series, and again particularly so for Germany and Italy, but declines between the middle of the sample and the end of the sample. Of further note, the correlations between the US and Japan appear low throughout the sample, suggesting a diversification opportunity.

With regard to the correlations between the US and the Northern Europe economies there appears to be little evidence of an upward trend in the nature of the relationship, although all the trend coefficients are positive they are also very small.[ii] As with the G7 results, there is an increase in the correlation coefficients between the start of the sample and the middle of the sample, and (with the exception of Iceland) a fall in the strength of correlations between the middle and end of the sample. Nevertheless, correlation coefficients remain relatively low again suggesting potential portfolio diversification opportunities. With regard to the correlations between the US and Southern Europe an almost identical pattern can be observed. That is, an increase in the strength of correlation between the start and middle of the sample, and a reduction in the strength of correlations between the middle and end of the sample (with the exception of Turkey which shows an increasing strength of correlations). Furthermore, at the end of the sample correlation remain low and close to zero for all series (except Spain for which the correlation coefficient nevertheless, is only 0.34).

Examining the time-varying correlations between the US and the Asian economies, again there is no evidence of trending behaviour with the trend coefficient very small for all series, and negative for three series.[iii] Furthermore, correlations are close to zero for all series at the end of sample. Moreover, in contrast to the results for the previous series, there is no general pattern of increasing correlations between the start and middle of the sample before a fall off in the strength of correlations, here no general pattern appears to exist. As before these results do suggest low correlations, with no evidence that they are increasing, suggesting opportunities for diversification. Finally, with regard to the correlations between the US and the Others there is some evidence of a positive trend in the correlations between the US and

Brazil but much less so with India while the correlations with Argentina appear to be declining in strength.

Turning to the regional correlation results here we see much more evidence of positive trending behaviour in the correlation coefficients. With regard to the European economies the correlations are high for a number of countries and have exhibited a strong positive relationship, in terms of increasing correlations throughout the sample particular, between Germany and Belgium, Finland, France, Greece, Italy, Netherlands, Spain, Sweden, Turkey and the UK. This is perhaps not surprising given the political and economic moves towards integration. Nevertheless, some correlations either remain relatively low or have shown a tendency to fall (or remain stable), for example with Austria, Denmark, Greece, Iceland, Ireland and Switzerland. For the Asian economies similar evidence is reported, that is for the majority of the series the strength of correlations increase from the beginning of the sample, through the middle of the sample to the end of the sample. This is particularly true for the correlations between Japan and Australia, China, Hong Kong, Korea, Singapore, Taiwan and Thailand. Whilst, for several series the strength of the correlations has risen to the middle of the sample but subsequently fall towards the end of the sample (Indonesia, Malaysia and the Philippines). Furthermore, the correlations remain relatively low for some economies, in particular China, Indonesia, Malaysia and the Philippines (albeit for China the correlations are slowly strengthening).

The results from this analysis suggest that the level of global integration is not as extensive as anecdotal evidence would suggest, correlations between the US and the rest of the world have not unambiguously trended upwards, whilst there is evidence to support such a relationship with other G7 economies, even here correlations have fallen in the past two years. With the remaining markets (both

European, Asian and Others) no such ubiquitous trending behaviour is observed. Within regional groupings there is more evidence of upwards trending correlations, however, again this is not a dynamic true to all markets considered and even within the Asia and Europe region there are relatively modest correlations. A further result of interest which deserves attention, is that for a significant number of series correlations have strengthened over the first half of the sample (1994-1999), a period associated with a bull market, and the run up to the late 1990's market bubble, while correlations have fallen over the second half of the sample (1999-2005), a period associated with the market crash following the bubble and subsequent recovery. The graphical evidence in Figure 2 (and upon request for the remaining series) shows that correlations generally remained constant during the market crash (2000-2003), and have fallen during the period of market recovery (2003-2005). This result contrasts slightly with previous results that have argued correlations typically increase in bear markets. In sum, these results of this section suggest that there remains room for portfolio managers to obtain diversified portfolios both within geographical regions and more globally. Similarly policy makers may need to take in account possibly not insignificant adjustment costs of co-ordinated action across regional markets.

IV. Monthly Realised Correlations.

Whilst most market participants would observe the market on a daily basis, it is also true that portfolio managers may make their decisions, that is, evaluate and adjust their portfolio's, on a monthly basis. Thus, in this section we calculate monthly correlations between the US and all other markets to sharpen the focus upon the one-month horizon. Furthermore, given that we have at our disposal daily data, rather than re-sampling at the monthly frequency we can make use of the daily data and

construct monthly realised correlations.[iv] Such realised variance measures are regarded as free from measurement error and provide a model-free nonparametric framework in which to examine time-variation in volatilities.

To set out the basic idea and intuition assume that the logarithmic $N \, x \, 1$ vector price process, p_t, follows a multivariate continuous time stochastic volatility diffusion:[v]

(5) $$dp = \mu_t \, dt + \sigma_t \, dW_t$$

where W_t denotes a standard N-dimensional Brownian motion, and σ the $N \, x \, N$ positive definite diffusion matrix. Further, normalising the unit time interval to represent one trading day, i.e. h=1, and conditional on the past realisations of μ_t and σ_t, the continuously compounded h-period returns $r_{t+h,h} \equiv p_{t+h} - p_t$ is then:

(6) $$r_{t+h,h} = \int_0^h \mu_{t+\tau} \, d\tau + \int_0^h \sigma_{t+\tau} \, dW(\tau)$$

which constitutes a decomposition into a predictable or 'drift' component of finite variation and a local martingale. Finally, using the theory of quadratic variation, increments to the quadratic return variation process are of the form:[vi]

(7) $$[r,r]_{t+h} - [r,r]_t = \int_0^h \sigma_{t+\tau} \, d\tau$$

which defines integrated volatility and provides a natural measure of the true latent h-period volatility. Moreover, the notion of integrated volatility already plays a central role in the stochastic volatility option pricing literature (Hull and White, 1987), where the price of an option typically depends on the distribution of the integrated volatility process for the underlying asset over the life of the option. This measure contrasts sharply with the common use of the squared h-period return as the simple ex post volatility measure which, although provides an unbiased estimate for realised integrated volatility, is an extremely noisy estimator. Furthermore, for longer

horizons any conditional mean dependence will tend to contaminate this latter variance measure, whereas the mean component is irrelevant for the quadratic variation.

Finally, the realised variance and covariance is given by:

(8) $$v_t^2 = \sum_{j=1,\ldots,[h/\Delta]} r_{t+j\Delta,\Delta}\, r'_{t+j\Delta,\Delta}$$

(9) $$v_{ik,t} = \sum_{j=1,\ldots,[h/\Delta]} r_{i,t+j\Delta,\Delta}\, r_{k,t+j\Delta,\Delta}$$

where $t=1,\ldots,T$, with T the total number of observations and $\Delta = 1/N$, with N the number of higher-frequency intervals. Therefore, the realised correlations are given by: $\rho_t = v_{ik,t} / \sqrt{v_{it}^2 \bullet v_{kt}^2}$.

Before proceeding to an examination of the plots of the time-varying correlations we present some relevant summary statistics for the realised variances, covariance and correlations in Table 5. In particular, Andersen et al (2003) have argued that realised volatility measures exhibit long memory and possible fractional behaviour. Whilst, the number of monthly observations is too few (136) to conduct fractional integration tests the results of the correlogram based Q-statistics do reveal significant evidence of long memory, while the ADF tests nonetheless support stationarity, thus, this is consistent with fractional integration behaviour. With regard to the realised covariances there is again evidence of long memory, that is, significant and large Q statistics, but ultimate stationarity (significant ADF statistics) for all covariances with the US, with the exception of all Asian (including India) countries and Iceland, which exhibit substantially shorter memory covariances. Finally, turning to the realised correlation measures, for all countries correlations with the US the Q-

statistics are lower than for the realised variance and covariance measures (with the exception Greece). This indicates that correlations have shorter-memory than both variances and covariances, and that in many cases the difference is substantial. This suggests, in the language of Engle and Kozacki (1993), the potential for common features (co-persistence) between variance and covariance. That is, where two variables exhibit a characteristic (i.e. long-memory) that a combination of them (the correlation variable) does not.[vii]

With regard to the nature of the time-varying realised correlations with the US we present graphical evidence in Figures 3-7, where a broadly similar pattern as that reported at the daily level is revealed. Examining the correlations for the G7 (Figure 3), there is a general upward trend for each country (especially France, Germany and Italy), but a noticeable fall in the strength of the correlations in the last two years of the sample. As noted above, this is a period where stock markets were generally rising following the bear market of the early 2000's. Figure 4 presents the realised correlations for the North Europe region, as with the results presented at the daily level there is little evidence of an upward trend in this relationship, although there is substantial variability with sub-periods that do exhibit strong positive correlations and weak positive or even negative correlations. Figure 5 presents the correlations between the US and Southern Europe there is evidence of an upward trend in the correlations for Greece and Portugal throughout the 1990's, but a levelling-off and indeed fall in the correlations during the 2000's, such that by the end of the sample the correlations are close to zero. For Spain and Turkey correlations do not appear to trend but vary around approximately 0.4 for Spain and 0.1 for Turkey. Examining the time-varying correlations between the US and the Asian economies (Figure 6), again there is no evidence of trending behaviour with correlations exhibiting substantial

fluctuation but around a relatively constant value. Finally, with regard to the correlations between the US and the Others (Figure 7) there is some evidence of a positive trend in the correlations between the US and Brazil and possibly India, but evidence of a declining trend with Argentina.

The results from this analysis, as with the daily analysis, suggest that correlations between the US and the rest of the world have not unambiguously trended upwards and that there remains room for portfolio managers to obtain diversified portfolios.

Does the Time-Variation Matter?

As a final exercise we briefly examine whether taking into account the time-variation noted above, in constructing monthly portfolios, reduces risk over an equally-weighted portfolio. That is for the G7 economies and each regional portfolio we compare an equally weighted portfolio, to one whose weights are determined by the estimated correlation coefficient from the latter analysis, such that those indices which have a correlation coefficient closest to –1 are given the greatest weight in the portfolio, the index with the second closest correlation coefficient to –1 is given the next highest weight in the portfolio and so on until the index with a correlation coefficient closest to 1 is given the lowest weight. In order to examine the level of risk within the equally-weighted portfolios and the portfolios whose weights are time-varying and determined by the time-varying correlation coefficient we plot in Figure 8 the 1% Value-at-Risk (VaR) of each portfolio. That is, the VaR is calculated as VaR=$N_\alpha \sigma V$, where σ is the standard deviation of the portfolio, V the value of the portfolio and N_α is the appropriate value to cut-off the 1% left tail in the normal distribution. In order to calculate the time-varying portfolio standard deviations, we

use the square root of a twelve-month moving average of squared portfolio returns. The results presented in Figure 8 suggest two interesting points, with the exception of Asia where VaR estimates are similar across the whole period. First, during normal period when volatility (risk) is low the VaR estimates are similar for both portfolio types. Second, when portfolio risk is high, or increasing, then the level of risk experienced by the equally weighted portfolio is greater than the level of risk experienced by the portfolio which has time-varying weights based upon the estimated correlation coefficient, with the exception of one period for the Others portfolio. This result supports the view expressed above that financial integration is not complete and suggests that even though correlation typically increase when volatility is high there still remains a role for active management in reducing the riskiness of a portfolio.

IV. Summary and Conclusions.

The analysis of financial market correlation and co-movement is an important issue for both policy makers and market participants, such as portfolio managers. That is, for policy makers financial convergence is important in assessing the potential costs from policy co-ordination and greater economic integration, while with regard to portfolio managers, financial correlations implies reductions in the benefits of portfolio diversification. The general view within the literature is that correlations between assets are time-varying, with particular increases in correlations at times of stress, however, it is less clear as to whether correlations amongst equity markets have trended upwards over time, although at present, the balance of empirical evidence suggests that is the case.

This paper seeks to reconsider this evidence using a data set of 33 daily international stock market indices. In particular, following the existing literature, we initially consider evidence from both cointegration and multivariate GARCH frameworks. In addition we also implement the more recent non-parametric realised variance method to model time-variation in the correlation coefficient. The benefit of incorporating this latter method is twofold. First, it enables examination of dynamic time-variation that the cointegration methodology does not, and second, it overcomes the shortfalls in the GARCH methodology with respect to parameterisation. Furthermore, it can be argued that the monthly frequency is more relevant to portfolio managers. Finally, we consider whether a portfolio based on the realised correlations from this latter exercise can reduce portfolio risk over an equally weighted portfolio.

Our results suggest the following pertinent points. First, examining the cointegration results, whilst there is evidence of co-movement and therefore convergence, nevertheless there is also evidence of multiple common stochastic trends, indicating that these stock markets are not fully converged. Second, examining the results for the time-varying correlations with the US, these results reveal that although there is a general upward trend in the correlation between the US and the G7 economies, the correlations appear to decline over the last two years. Third, with regard to the correlations between the US and all other economies there appears to be little evidence of an upward trend in the nature of the relationship, although there is wide variability and sub-periods that do exhibit both positive and negative correlations. Fourth, on a more regional basis, correlations do exhibit much greater evidence of positive trending behaviour, for example, in the Asian economies this is perhaps most prevalent between Japan and Hong Kong, Korea, Singapore and Taiwan, while with regard to the European economies the correlations are high for a

number of countries and in particular, between Germany and Belgium, Finland, France, Italy, Netherlands, Spain, Sweden, Turkey and the UK. Nevertheless, the correlations remain relatively low for some economies, in particular between Japan and China, Indonesia, Malaysia and the Philippines, and Germany and Greece and Iceland. Fifth, the results regarding the correlations with the US are supported by analysis at the monthly level using realised correlation analysis, which provides for a measurement-free method of constructing variances. Furthermore, a simple exercise which examines the riskiness of equally-weighted portfolios and those constructed on the basis of the time-varying realised correlations supports a role for active portfolio management in reducing portfolio risk.

In sum, the results from this analysis suggest that correlations between the US and the rest of the world have not unambiguously trended upwards, and whilst there is evidence to support such a relationship with other G7 economies, even here correlations have fallen in the past two years. With the remaining markets (both European, Asian and Others) no such general trending behaviour is observed. Within regional groupings there is more evidence of upwards trending correlations, however, again this is not a dynamic true to all markets considered and even within the Asia and Europe region there are relatively modest correlations. These results suggest that the degree of market co-movement has perhaps been overstated and that there remains room for portfolio managers to obtain diversified portfolios both within geographical regions and more globally. Similarly policy makers may need to take in account possibly not insignificant adjustment costs of co-ordinated action across regional markets.

References.

Aggarwal, R and Kyaw, NA (2005). 'Equity market integration in the NAFTA region: Evidence from unit root and cointegration tests', International Review of Financial Analysis, 14, 393-406.

Andersen T G, Bollerslev, T, Diebold, F X and Ebens, H (2001) 'The Distribution of Realised Stock Return Volatility', Journal of Financial Economics, 61, 43-76.

Andersen T G, Bollerslev, T, Diebold, F X and Labys, P (2003), 'The distribution of realized exchange rate volatility', Journal of the American Statistical Association, 96, 42-55.

Andersen T G, Bollerslev, T, Diebold, F X and Labys, P (2003) 'Modelling and Forecasting Realised Volatility', Econometrica, 71, 579-625.

Andersen T G, Bollerslev, T, Diebold, F X and Wu, J (2004) 'Realized beta: Persistence and Predictability', Center for Financial Studies, working paper No. 2004/16.

Barndorff-Nielsen, OE and Shephard, N (2003), 'Econometrics analysis of realized covariation: High frequency covariance, regression and correlation in financial economics', Nuffied Collegee, Oxford, working paper.

Berben RP and Jansen, WJ (2005), 'Comovement in international equity markets: A sectoral view', Journal of International Money and Finance, 24, 832-857.

Bollerslev, T, Engle, R F and Wooldridge, J (1988), 'A capital asset pricing model with time-varying covariances', Journal of Political Economy, 96, 116-131.

Cheung, Y-W and Lai, K S (1993), 'A fractional cointegration analysis of purchasing power parity', Journal of Business and Economic Statistics, 11, 103-112.

Corhay, A, Rad, AT and Urbain, JP (1993), 'Common Stochastic Trends in European Stock Markets', Economics Letters, 42, 385–90.

Engle, R F and Kozicki, S (1993), 'Testing for common features', Journal of Business and Economic Statistics, 11, 369-383.

Engle, R F and Kroner, K (1995), 'Multivariate simultaneous generalised ARCH', Econometric Theory, 11, 122-150.

Erb, C, Harvey, C and Viskanta, T (1994), 'Forecasting international equity correlations', Financial Analysts Journal, 50, 32-45.

Forbes, K and Rigobon, R (2002), 'No contagion, only interdependence: Measuring stock market co-movements', Journal of Finance, 57, 2223-2261.

Fraser, P and Oyefeso, O (2005), 'US, UK and European stock market integration', Journal of Business Finance and Accounting, 32, 161-181.

Goetzmann, WN, Li, L and Rouwenhorst, KG (2001), 'Long-term global market correlations', NBER working paper No. 8612.

Johansen, S (1996) Likelihood-Based Inference in Cointegrated Vector Auto-Regressive Models, Oxford University Press, Oxford.

Karolyi, GA and Stulz, RM (1996), 'Why do markets move together? An investigation of US-Japan stock return co-movements', Journal of Finance, 51, 951-986.

Kasa, K (1992), 'Common Stochastic Trends in International Stock Markets', Journal of Monetary Economics, 29, 95–124.

Kim, SJ, Moshirian, F and Wu, E (2005), 'Dynamics stock market integration driven by the European Monetary Union: An empirical analysis', Journal of Banking and Finance, 29, 2475-2502.

King, M and Wadhwani, S (1990), 'Transmission of volatility between stock markets', Review of Financial Studies, 3, 5-33.

King, M, Sentana, E and Wadhwani, S (1994), 'Volatility and links between national stock markets', Econometrica, 62, 901-933.

Longin, F and Solnik, B (1995), 'Is the correlation in international equity returns constant: 1960-1990?' Journal of International Money and Finance, 14, 3-26.

Ragunathan, V and Mitchell, H (1997), 'Modelling the time-varying correlations between national stock market returns', Royal Melbourne Institute of Technology, Department of Economics and Finance, working paper.

Rangvid, J (2001), 'Increasing convergence among European stock markets? A recursive common stochastic trends analysis', Economic Letters, 71, 383-389.

Roll, R (1989), 'Price volatility, international market links, and their implications for regulatory policies', Journal of Financial Services Research, 211-246.

Schwert, G W (1989), 'Why does stock market volatility change over time?', Journal of Finance, 44, 1115-1153.

Schwert, G W (1990), 'Stock market volatility and the crash of '87', Review of Financial Studies, 3, 77-102.

Schwert, G W and Sequin, P J (1990), 'Heteroscedasticity in stock returns', Journal of Finance, 45, 1129-1155.

Stock, J M and Watson, M, (1988), Testing for common trends, Journal of the American Statistical Association, 83, 1097-1107.

Taylor, MP and Tonks, I (1989), 'The Internationalisation of Stock Markets and the Abolition of U.K. Exchange Control', Review of Economics and Statistics, 71, 332–36.

Wahab, M W (1995), 'Conditional dynamics and optimal spreading in the precious metals futures markets', Journal of Futures Markets, 15, 131-166.

Table 1. Data Descriptive Statistics					
Country	Mean	Std Dev	Skew	Kurt	ADF
	G7				
Canada	0.00026	0.0095	-0.7109	9.7989	-1.27
France	0.00019	0.0139	-0.0782	5.5764	-1.15
Germany	0.00028	0.0086	-0.7096	7.4148	-1.55
Italy	0.00030	0.0130	-0.1531	5.6267	-1.29
Japan	-0.00015	0.0141	0.0324	5.4555	-1.13
UK	0.00012	0.0108	-0.1717	5.9237	-1.38
US	0.00031	0.0108	-0.1074	6.6473	-1.84
	North Europe				
Austria	0.00028	0.0098	-0.6893	8.2194	0.45
Belgium	0.00025	0.0109	0.2430	8.7696	-1.27
Denmark	0.00037	0.0107	-0.2828	5.4889	-0.86
Finland	0.00048	0.0203	-0.4643	9.8279	-1.40
Iceland	0.00082	0.0065	-0.2072	11.9825	-0.27
Ireland	0.00039	0.0099	-0.5550	8.2002	-1.26
Netherlands	0.00021	0.0142	-0.1059	7.3175	-1.51
Sweden	0.00035	0.0150	0.1006	6.2439	-1.49
Switzerland	0.00023	0.0121	-0.1461	7.2355	-1.36
	South Europe				
Greece	0.00037	0.0160	-0.0341	7.0603	-1.15
Portugal	0.00020	0.0104	-0.6488	10.7766	-1.34
Spain	0.00031	0.0136	-0.1817	5.6344	-1.31
Turkey	0.00160	0.0303	-0.0787	6.6979	-1.21
	Asia				
Australia	0.00021	0.0076	-0.5574	10.1718	-0.61
China	0.00011	0.0217	1.8526	32.4540	-1.63
Hong Kong	0.00004	0.0169	0.0859	13.0528	-2.24
Indonesia	0.00019	0.0162	0.0741	11.9733	-2.16
Korea	0.00002	0.0203	-0.0896	6.7453	-1.85
Malaysia	-0.00013	0.0168	0.5588	41.5589	-2.05
Philippines	-0.00019	0.0149	0.7475	15.0640	-1.89
Singapore	0.00000	0.0187	0.2113	13.7541	-2.23
Taiwan	-0.00002	0.0162	-0.1137	5.5786	-2.28
Thailand	-0.00031	0.0176	0.4337	7.2827	-1.75
	Others				
Argentina	0.00047	0.0215	0.3929	10.3762	-0.28
Brazil	0.00142	0.0261	0.5888	13.7346	-1.32
India	0.00024	0.0155	-0.3059	7.2622	-1.38
Notes: ADF lags chosen by AIC (5%CV –2.86)					

Table 2. Cointegrating Relationships.				
Trace Statistic for Cointegrating Rank				
Hypothesised Rank (*r*)	Eigenvalue	Likelihood Ratio	5% Critical Value	1% Critical Value
G7				
r=0	0.0186	130.77	124.24	133.57
r=1	0.0091	75.52	94.15	103.18
r=2	0.0064	48.50	68.52	76.07
North Europe				
r=0	0.0189	208.05	192.89	204.95
r=1	0.0161	151.68	156.00	168.36
r=2	0.0100	103.95	124.24	133.57
South Europe				
r=0	0.0164	67.50	47.21	54.46
r=1	0.0047	18.63	29.68	35.65
r=2	0.0010	4.63	15.41	20.04
Asia				
r=0	0.0274	343.57	277.71	293.44
r=1	0.0246	261.62	233.13	247.18
r=2	0.0181	188.30	192.89	204.95
r=3	0.0149	134.54	156.00	168.36
Other				
r=0	0.0225	78.16	29.68	35.65
r=1	0.0037	11.11	15.41	20.04
r=2	8.60e-05	0.25	3.76	6.65
Maximum-Eigenvalue Statistic for Cointegrating Rank				
Hypothesised Rank (*r*)	Eigenvalue	Likelihood Ratio	5% Critical Value	1% Critical Value
G7				
r=0	0.0186	55.25	45.28	51.57
r=1	0.0091	27.02	39.37	45.10
r=2	0.0064	18.95	33.46	38.77
North Europe				
r=0	0.0189	56.37	57.12	62.80
r=1	0.0161	47.73	51.42	57.69
r=2	0.0100	29.63	45.28	51.57
South Europe				
r=0	0.0164	48.87	27.07	32.24
r=1	0.0047	14.00	20.97	25.52
r=2	0.0010	3.08	14.07	18.63
Asia				
r=0	0.0274	81.95	68.83	75.95
r=1	0.0246	73.32	62.81	69.09
r=2	0.0181	53.76	57.12	62.80
r=3	0.0149	44.38	51.42	57.69
Others				
r=0	0.0225	67.06	20.97	25.52
r=1	0.0037	10.85	14.07	18.63
r=2	8.60e-05	0.25	3.76	6.65
Notes: Cointegration tests based upon a constant term in the cointegrating equation and a constant and single lag in the test VAR.				

Table 3. Correlation Coefficients with the US					
Country	Sample Mean	1st 130 Obs. Mean	Middle 130 Obs. Mean	Last 130 Obs. Mean	Beta
	G7				
Canada	0.55	0.56	0.59	0.41	0.005
France	0.38	0.29	0.44	0.33	0.006
Germany	0.37	0.17	0.45	0.34	0.015
Italy	0.33	0.08	0.42	0.30	0.011
Japan	0.08	0.05	0.03	0.06	0.004
UK	0.39	0.33	0.40	0.33	0.003
US					
	North Europe				
Austria	0.15	0.11	0.26	0.20	0.003
Belgium	0.31	0.16	0.39	0.22	0.004
Denmark	0.22	0.07	0.24	0.16	0.005
Finland	0.23	0.06	0.24	0.13	0.007
Iceland	-0.01	-0.08	-0.03	0.08	0.003
Ireland	0.22	0.20	0.21	0.19	0.002
Netherlands	0.37	0.25	0.43	0.33	0.007
Sweden	0.33	0.29	0.37	0.22	0.005
Switzerland	0.26	0.18	0.41	0.14	0.005
	South Europe				
Greece	0.08	-0.04	0.06	-0.01	0.007
Portugal	0.20	-0.02	0.24	0.04	0.008
Spain	0.36	0.37	0.41	0.34	0.006
Turkey	0.06	0.01	0.06	0.11	0.004
	Asia				
Australia	0.08	0.05	0.08	0.11	-0.001
China	-0.03	0.05	-0.04	0.01	0.001
Hong Kong	0.11	0.01	0.08	0.12	0.001
Indonesia	0.04	-0.002	0.05	-0.05	0.001
Korea	0.09	0.06	0.07	0.10	0.003
Malaysia	0.03	0.12	0.07	-0.01	-0.003
Philippines	0.05	-0.04	0.04	0.04	-0.002
Singapore	0.12	0.14	0.03	0.11	0.002
Taiwan	0.04	0.01	-0.04	0.09	0.004
Thailand	0.06	0.09	0.12	-0.03	0.0001
	Others				
Argentina	0.36	0.40	0.32	0.30	-0.006
Brazil	0.42	0.27	0.50	0.44	0.007
India	0.05	0.002	-0.03	0.09	0.003
Notes: Entries are correlation coefficients obtained by the BV-GARCH model, see Section III.					

Table 4. Regional Correlation Coefficients					
Country	Sample Mean	1st 130 Obs. Mean	Middle 130 Obs. Mean	Last 130 Obs. Mean	Beta
	Correlations with Germany				
Austria	0.49	0.54	0.49	0.60	-0.006
Belgium	0.61	0.54	0.60	0.67	0.004
Denmark	0.53	0.56	0.53	0.60	-0.001
Finland	0.58	0.47	0.59	0.63	0.006
France	0.73	0.61	0.78	0.91	0.016
Greece	0.18	0.02	0.11	0.18	0.012
Iceland	0.03	0.05	0.08	0.07	0.00002
Ireland	0.47	0.43	0.45	0.42	-0.001
Italy	0.65	0.40	0.73	0.83	0.019
Netherlands	0.75	0.63	0.78	0.87	0.009
Portugal	0.43	0.30	0.45	0.39	0.007
Spain	0.66	0.49	0.68	0.79	0.013
Sweden	0.65	0.53	0.68	0.77	0.010
Switzerland	0.51	0.47	0.58	0.43	0.007
Turkey	0.14	-0.03	0.17	0.27	0.006
UK	0.64	0.47	0.72	0.74	0.011
	Correlations with Japan				
Australia	0.38	0.31	0.43	0.46	0.006
China	0.03	-0.04	0.02	0.08	0.002
Hong Kong	0.40	0.17	0.43	0.45	0.009
Indonesia	0.19	0.14	0.23	0.19	0.003
Korea	0.30	0.20	0.26	0.53	0.019
Malaysia	0.24	0.10	0.25	0.23	0.005
Philippines	0.19	0.08	0.30	0.21	0.003
Singapore	0.36	0.15	0.45	0.49	0.007
Taiwan	0.16	0.05	0.17	0.23	0.011
Thailand	0.22	0.05	0.27	0.30	0.005
Notes: Entries are correlation coefficients obtained by the BV-GARCH model, see Section III.					

Table 5. Realised Data Descriptive Statistics									
Country	Realised Variance			Realised Covariance			Realised Correlation		
	Q1	Q12	ADF	Q1	Q12	ADF	Q1	Q12	ADF
	G7								
Canada	38.26	162.73	-4.49	31.01	106.26	-6.91	6.09	37.35	-9.42
France	62.29	135.26	-5.10	54.03	162.42	-5.54	6.13	57.90	-9.30
Germany	59.46	186.24	-5.25	64.39	268.36	-3.53	37.96	151.64	-3.13
Italy	26.85	51.15	-7.18	37.06	149.35	-6.52	12.76	113.36	-8.49
Japan	24.57	47.96	-7.57	6.39	33.96	-9.32	0.29	13.03	-11.22
UK	46.48	119.12	-5.94	40.22	126.37	-6.31	0.28	9.64	-11.02
US	48.47	147.31	-5.87	-	-	-	-	-	-
	North Europe								
Austria	35.57	84.57	-6.61	16.15	33.06	-8.10	1.97	12.98	-10.22
Belgium	41.95	100.21	-6.22	45.92	136.72	-4.23	10.92	59.92	-8.62
Denmark	33.29	81.86	-6.74	31.67	79.71	-6.87	9.21	19.11	-8.84
Finland	38.45	122.12	-6.40	30.35	82.08	-6.95	0.32	24.14	-10.99
Iceland	27.03	87.13	-4.99	0.09	20.94	-11.23	2.15	13.90	-10.16
Ireland	25.35	81.22	-7.29	11.52	29.66	-8.56	0.44	9.24	-12.16
Netherlands	59.63	157.76	-5.25	54.27	182.29	-5.53	11.18	38.95	-8.59
Sweden	37.05	131.70	-4.39	44.74	111.92	-6.03	7.85	21.48	-8.97
Switzerland	41.76	78.34	-6.21	41.57	105.61	-6.22	2.67	38.48	-3.82
	South Europe								
Greece	29.84	254.22	-1.60	4.67	43.25	-5.85	8.22	52.46	-9.00
Portugal	40.97	133.13	-6.25	35.82	97.45	-6.58	14.24	94.62	-8.29
Spain	49.54	109.62	-5.77	43.67	118.80	-6.11	4.44	26.06	-8.20
Turkey	26.83	65.85	-5.22	3.10	25.59	-9.92	2.76	13.37	-8.44
	Asia								
Australia	5.82	21.08	-8.20	0.01	16.85	-11.65	0.13	5.28	-11.33
China	10.96	47.48	-8.16	0.38	11.75	-10.94	0.39	12.99	-10.94
Hong Kong	19.60	77.21	-8.03	1.52	21.06	-10.38	0.37	13.31	-10.97
Indonesia	59.99	242.42	-8.77	1.95	38.75	-8.59	1.00	15.38	-10.49
Korea	73.85	281.22	-10.50	0.48	24.87	-10.89	0.12	13.46	-11.91
Malaysia	7.81	42.61	-8.08	3.72	8.32	-13.63	2.26	19.00	-10.04
Philippines	17.47	78.83	-8.69	1.99	9.18	-10.73	0.38	8.20	-12.27
Singapore	35.49	120.47	-8.76	0.45	13.68	-7.95	0.06	9.18	-11.34
Taiwan	23.40	36.96	-8.81	0.00	7.46	-9.83	0.00	5.54	-11.49
Thailand	37.74	230.58	-8.19	0.02	30.85	-8.65	0.54	15.11	-12.18
	Others								
Argentina	27.86	46.98	-7.13	27.05	59.14	-7.19	16.50	41.38	-7.98
Brazil	24.18	74.49	-7.44	29.78	71.05	-6.99	12.95	76.75	-8.44
India	19.26	68.45	-7.79	0.86	12.22	-10.66	1.97	18.68	-10.25

Notes: Q refers to serial correlation Q-statistics of lags one and twelve.

Figure 1. Rolling Cointegration Tests

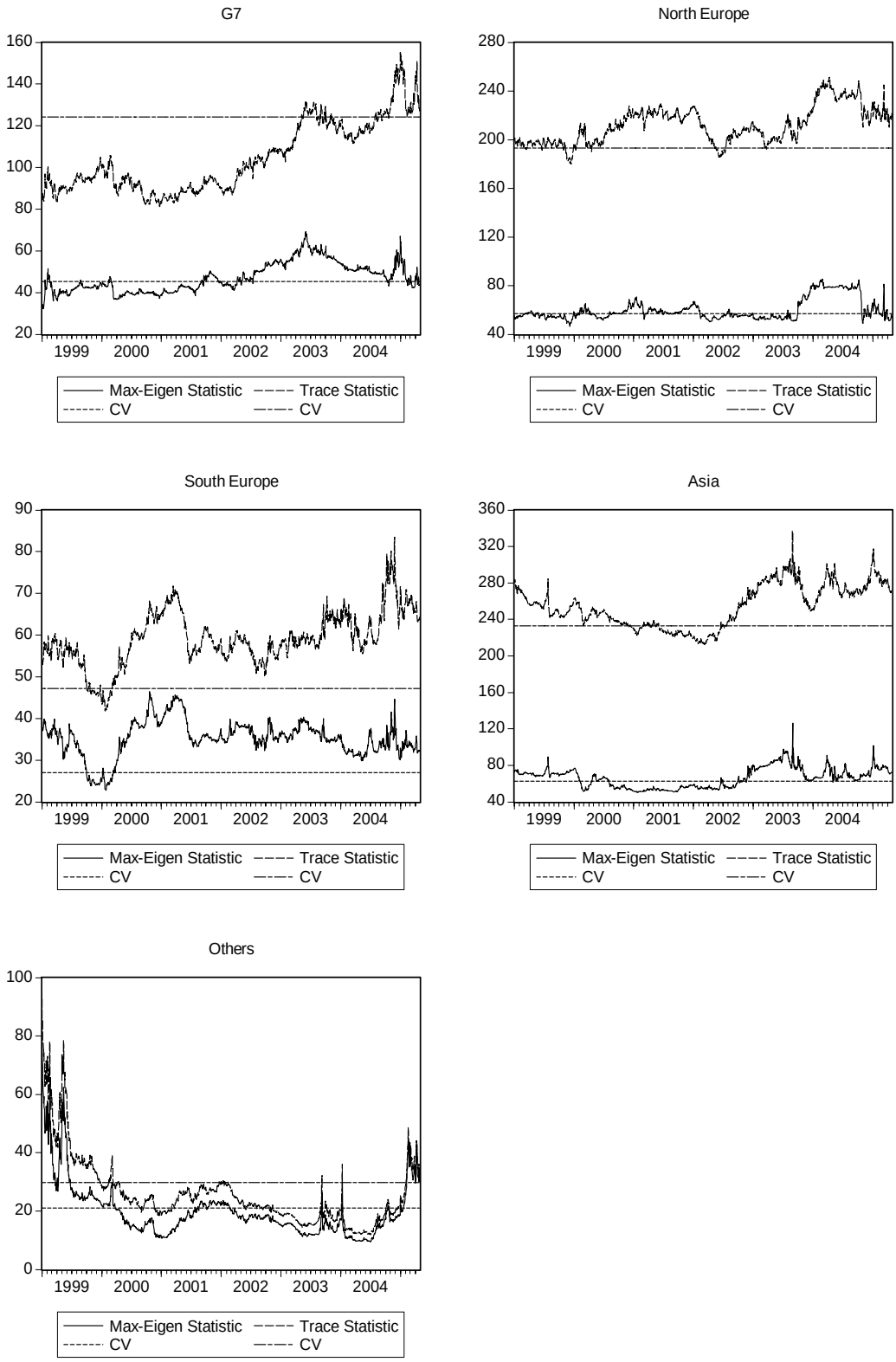


Figure 2. Time-Varying Correlations US and other G7

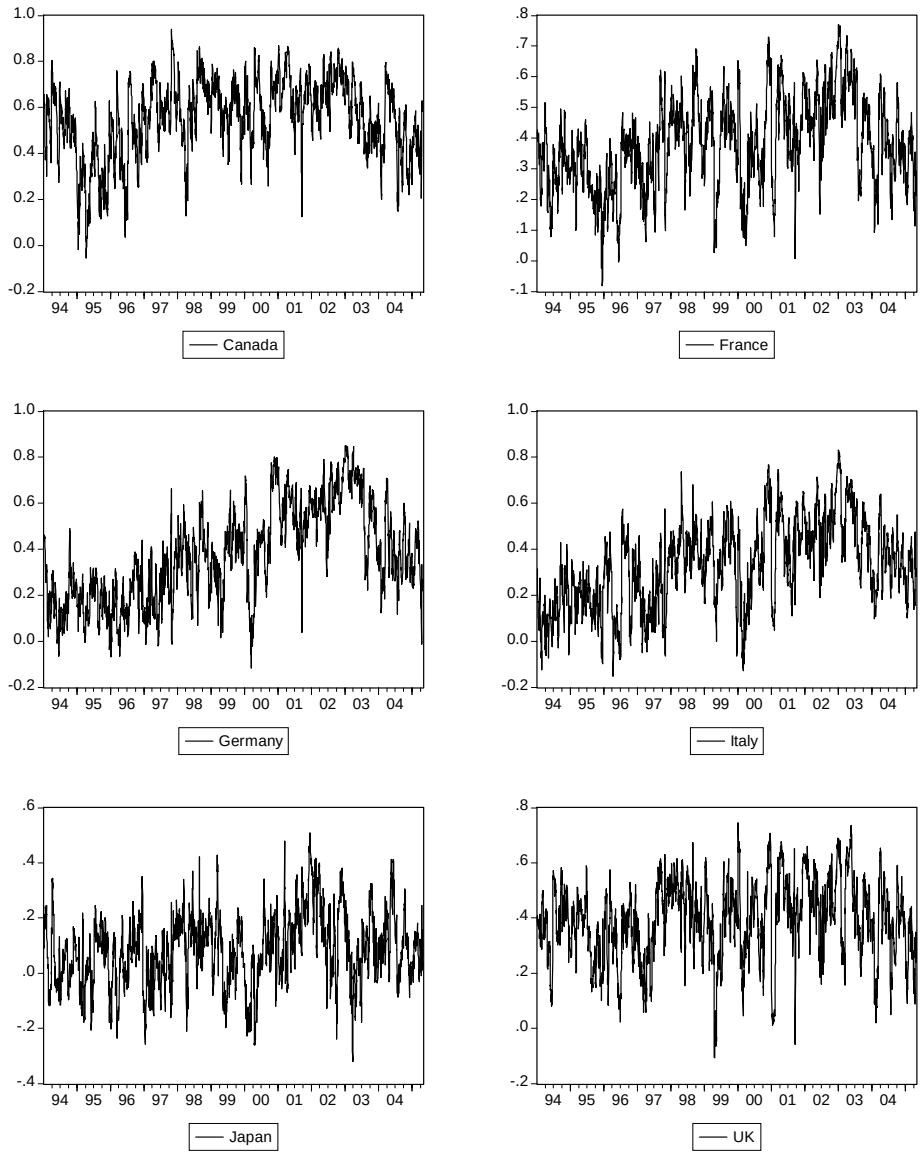


Figure 3. Realised Correlations US and other G7

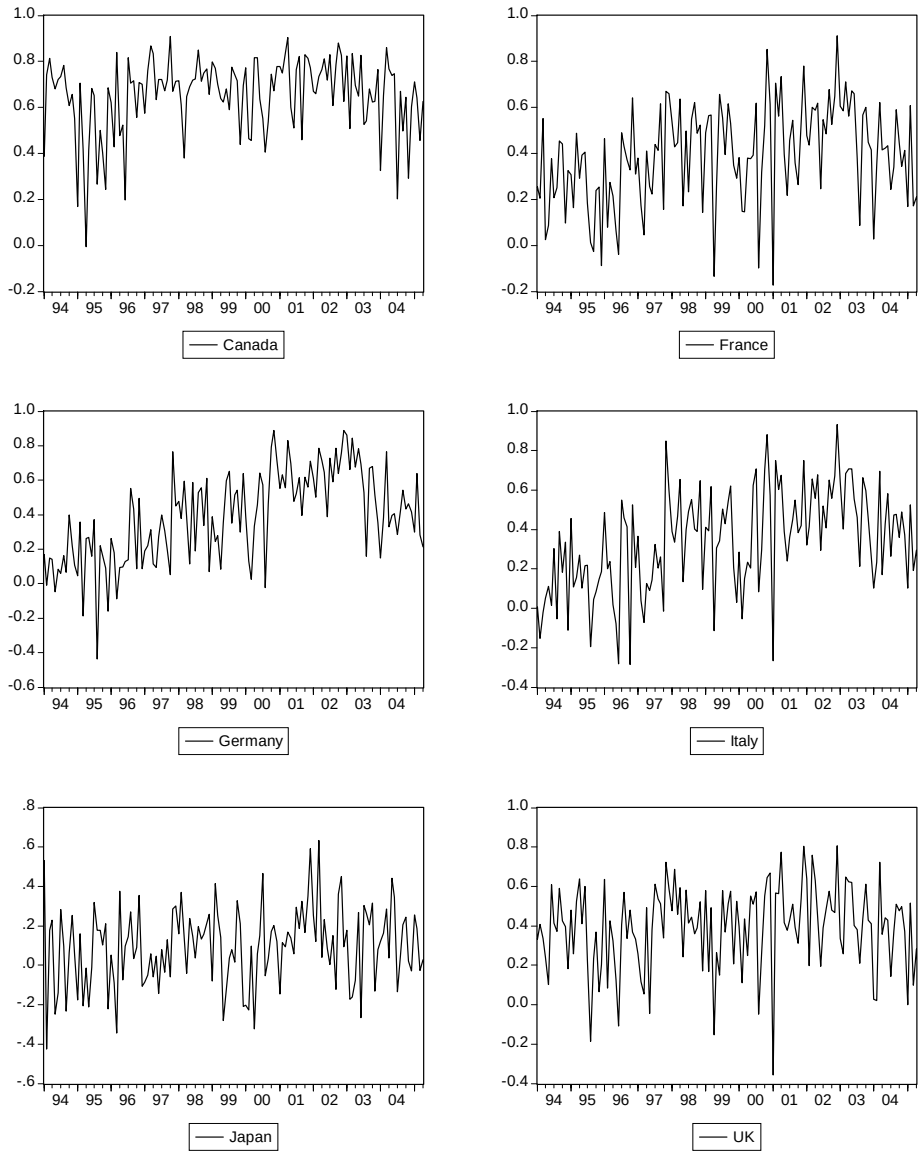


Figure 4. Realised Correlations US and North Europe

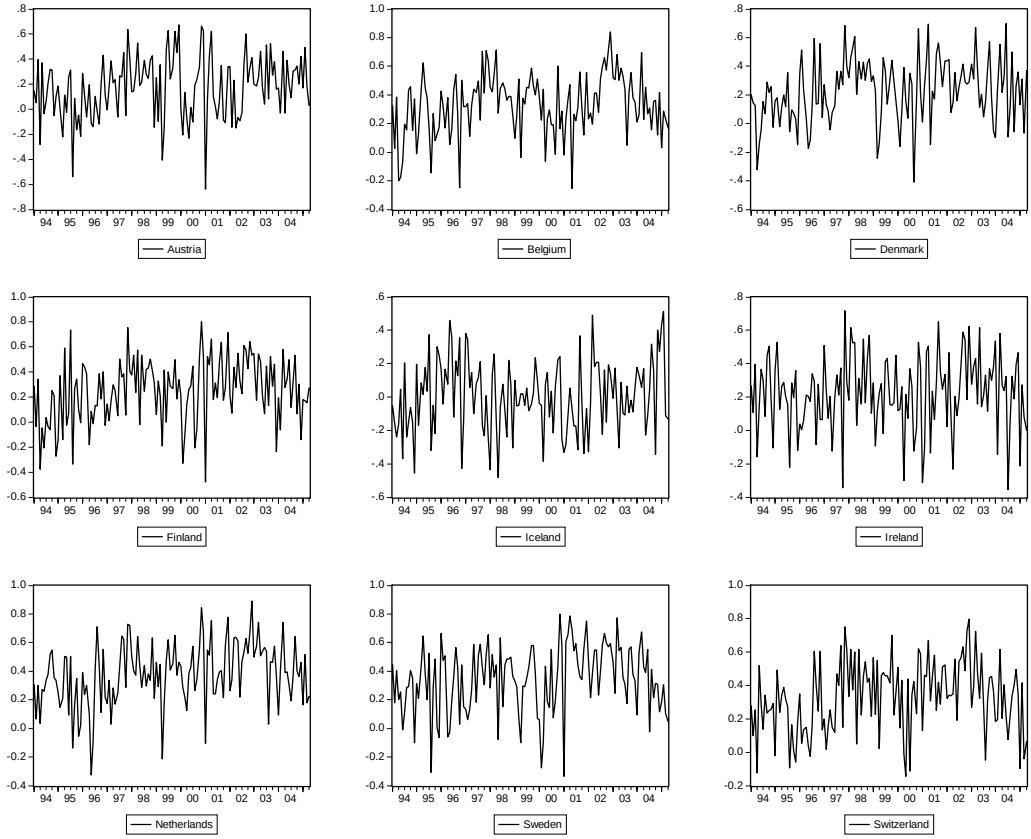


Figure 5. Realised Correlations US and South Europe

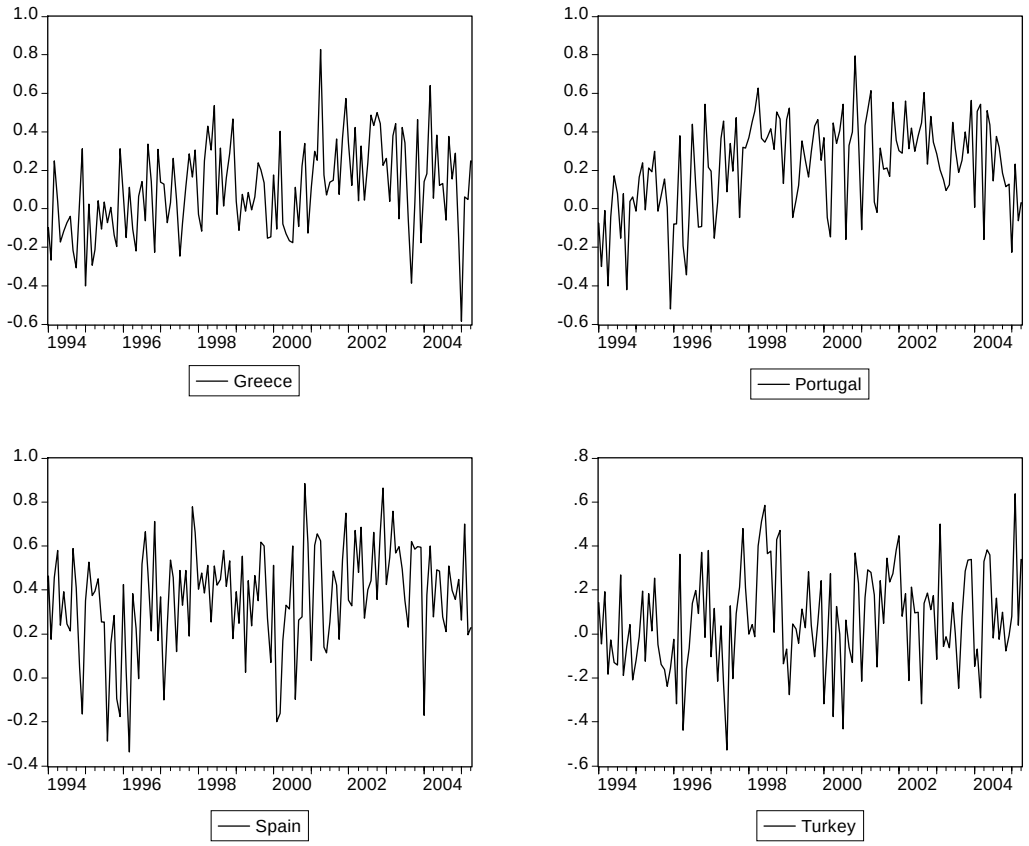


Figure 6. Realised Correlations US and Asia

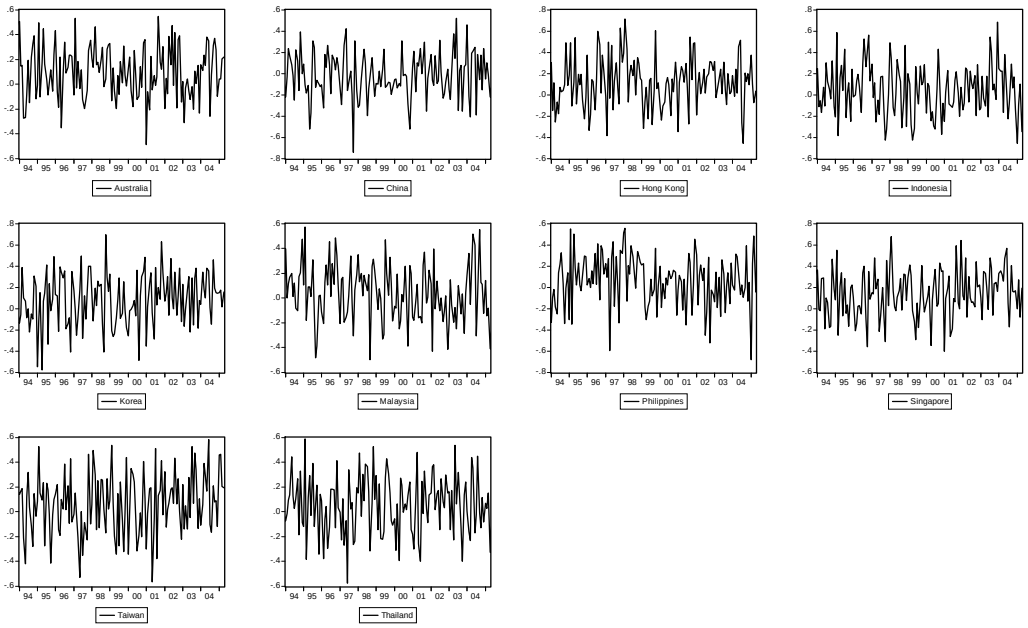


Figure 7. Realised Correlations US and Others

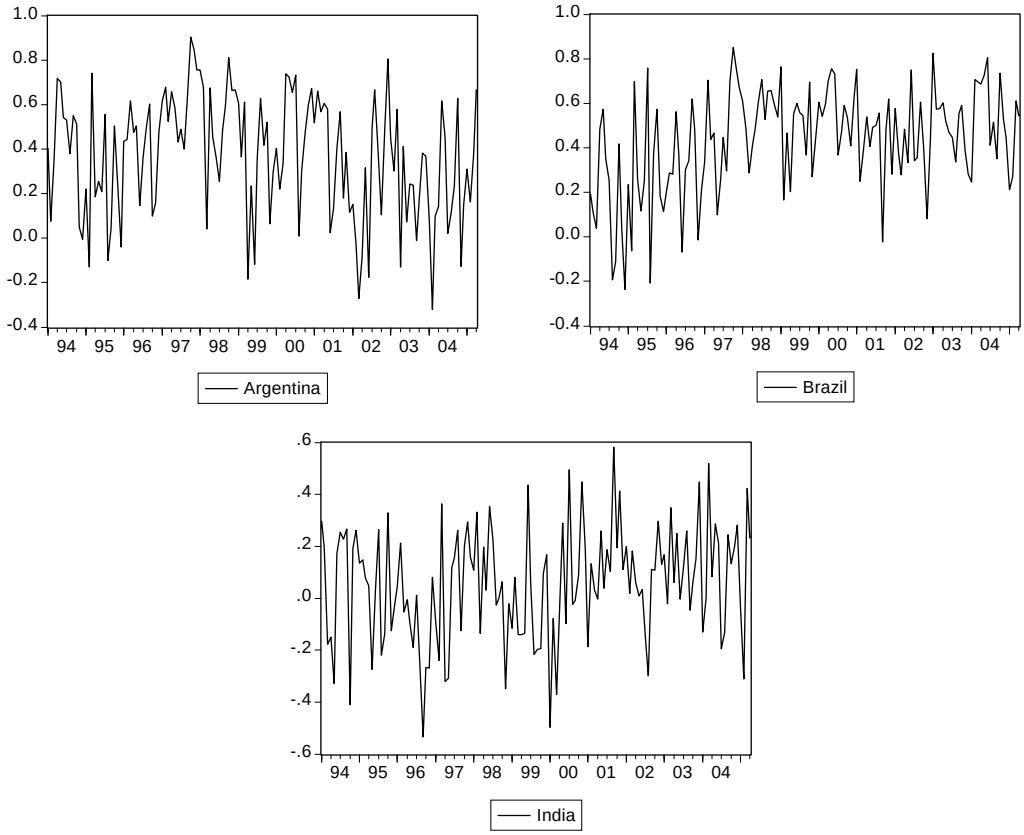
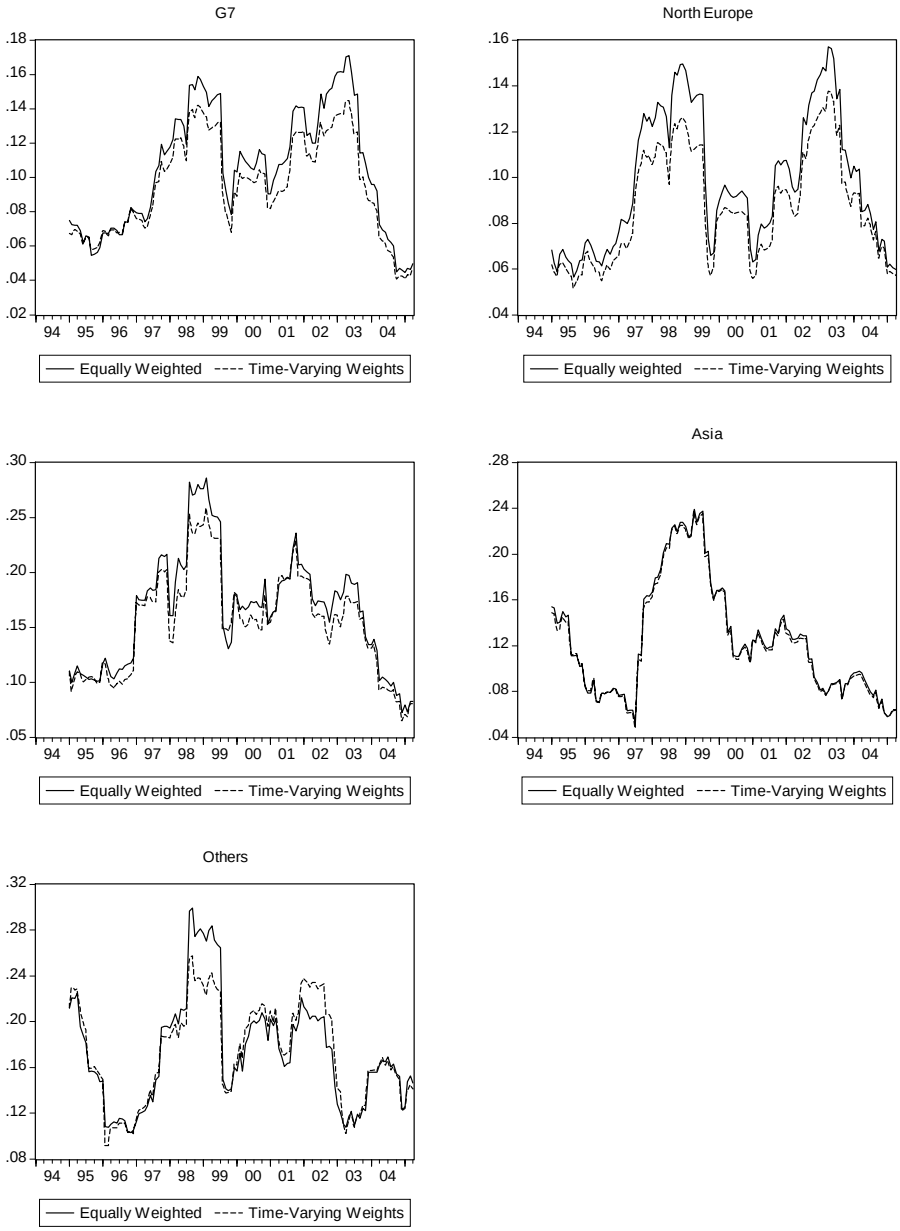


Figure 8. Portfolio Value-at-Risk



Notes:

[i] Equivalent plots for the correlations between the US and the remaining groupings and the regional correlations are available from the authors.

[ii] The graphical evidence (not reported) shows wide variability in the time-varying correlations and sub-periods that do exhibit both positive and negative trends.

[iii] The graphical evidence suggests correlations generally fluctuate within a broad band of around –0.3 to 0.3.

[iv] Of course, the use of daily data to model lower frequency data is not new and goes back to Schwert (1989, 1990) and Schwert and Sequin (1990) who use daily data to calculate monthly volatility.

v. The theoretical justification for constructing such realised correlations(that is, realised covariances and variances), and for a more thorough treatment of the issues raised, see Andersen, Bollerslev, Diebold and Labys (2001, 2003), Andersen, Bollerslev, Diebold and Ebens (2001) and Barndorff-Nielsen and Shephard (2003).

vi. The quadratic variation process measures the realised sample path variation of the squared returns process and suggests that we may approximate the quadratic variation by summing high-frequency squared returns (for further details see the papers cited in endnote ii).

[vii] If we accept the possibility of fractional integration in realised variances and covariances, then this suggests the presence of fractional cointegration (Cheung and Lai, 1993). A result similar to this was reported by Andersen et al (2004) in the context of realised CAPM betas.