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Temporal Links Between Asia-Pacific and International Stock Markets

George Milunovich¹
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I examine interdependencies between the national stock markets of Australia, Japan, the US and the UK over the period 1971-2005, and consider their implications for international portfolio diversification. It appears that portfolio gains associated with diversification across the Anglo-American markets declined over the 1989 – 2003 period, while diversification gains of investing in Japan have remained relatively steady over the entire sample. Like volatility, all conditional correlations increase in magnitude when associated with bear markets, which suggests that international diversification fails to provide adequate risk-protection when it is needed the most, during periods of financial distress.

JEL Classifications: G15, G11, C32
Keywords: Stock Market Interdependencies, Asia-Pacific Region, VECM, MGARCH, Portfolio Risk

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1. Introduction

Recent developments in international finance such as financial deregulation, integration of capital markets and financial contagion have been suggested to strengthen dependencies between national stock markets and hence reduce risk-reduction gains achieved through international diversification (e.g. Longin and Solnik, 1995; Koutmos and Booth, 1995; Billio and Pelizzon, 2003). In the light of this argument, I re-examine interdependencies between the national stock markets of the Asia-Pacific region, as represented by Japan and Australia, and the two largest international markets: the US and the UK. Further, I also consider implications of the linkages uncovered here in the context of international portfolio diversification and risk management.

The empirical method used here consists of a combination of several econometric time-series models. I specify the mean process as a vector error correction model (VECM), conditional volatilities as a GJR model of Glosten, Jagannathan and Runkle (1993 and the conditional correlation matrix as a generalized dynamic conditional correlation (ADCC) specification of Cappiello, Engle and Sheppard (2004). Further, I explicitly account for asymmetric effects associated with negative news shocks, first reported by Black (1976) and Christie (1982), in all components of the second moment matrix, including conditional correlations, conditional volatility and volatility spillovers.

I estimate the VECM-ADCC model on weekly stock market index returns over the period 26 November 1971 – 1 April 2005 and find that the stock markets of the Asia-Pacific region (i.e. Australia and Japan) and the markets of the US and the UK are cointegrated with one cointegrating vector. The explanatory power of a VECM model for weekly returns is small, between 2 percent for the US and 6 percent for the Australian market. Although the Australian and Japanese markets adjust most rapidly to deviations from the long-run equilibrium, they do so at a rate
of about 1.4 per cent per week. Thus it appears that, due to small speed of adjustment coefficients and low explanatory power of the VECM, cointegration is unlikely to significantly diminish international diversification benefits over shorter holding periods. However, as pointed out by Philaktis and Ravazzolo (2005) and Kasa (1992) the long-run relationship is likely to reduce diversification gains over longer holding periods.

In the conditional second moment, I find bidirectional volatility spillovers between the US and UK and unidirectional spillovers from the US to Australia and Japan. The spillovers to Australia and the UK are statistically significant only when related to bad news in the US, while the spillover to Japan is insensitive to the sign of the US news shock. These findings suggest that a portion of each country’s market risk is due to lagged transmissions of international risk and is thus predictable and should be used in risk management application such as value at risk calculations.

Conditional correlations exhibit time varying behaviour and asymmetric responses to negative news. The Australian stock market displays an upward trend in conditional correlation with the US over the period 1989-2002 and with the UK between 1993 and 2002. These correlations have since stabilised. On the other hand, none of the market pairs that include the Japanese market shows a sustained pattern in correlation, although they follow similar paths. Like volatility, all conditional correlations increase in magnitude when associated with negative news.

In order to demonstrate the effects of the dependencies reported here I estimate correlations between any two elements of the realised conditional covariance matrix as estimated by the ADCC-GJR models. It appears that all such pair-wise correlations increase over periods of financial crisis when compared with tranquil periods. For example, the largest increase over a crisis period of eighteen times its tranquil period value is found in the correlation coefficient between the realised conditional variances of the UK and Japanese markets. Similarly the correlation coefficient between the UK volatility and the Japan-UK conditional correlation rises

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2 All index price series are expressed in US dollars.
from -18 per cent to 61 percent. Thus, as the elements of the conditional covariance matrix become more strongly correlated, over the periods of bear markets, the amount of international diversification benefits diminishes when it is needed the most and hence international portfolio risk increases.

The rest of the paper is organised as follows: Section 2 reviews some relevant literature on linkages between national stock markets. The econometric methodology is discussed in Section 3 while Section 4 describes the dataset and presents summary statistics together with the unit root and cointegration tests. Model estimates are presented in Section 5 and Section 6 provides conclusions to this chapter.

2. Literature Review: International Stock Market Linkages

I review the literature under four rubrics. Section 2.1 surveys work on contemporaneous correlations and long-run cointegration. Lagged returns transmission mechanisms are reviewed in Section 2.2 and volatility spillovers literature is surveyed in Section 2.3. Asymmetric effects are discussed in Section 2.4.

2.1 Contemporaneous Correlations

Kaplanis (1988) is amongst the first to test inter-temporal stability in correlations and covariances on major international markets using monthly data. She reports a stable correlation structure across four time periods of equal length (46 months) between 1967 and 1982. However, she rejects the null of inter-temporal stability in covariance matrices at the 5 percent significance level for any two time sub-periods. Ratner (1992) also claims that the international correlations are stationary over the period 1973-1989. Meric and Meric (1989) find that the longer the time period, the greater the degree of stability in correlations. They use data for seventeen national stock markets covering the period 1973-1987. Koch and Koch (1991) reveal growing market interdependence in daily data on eight national stock indices. Similarly, Von Furstenberg and Jeon (1989) identify increases in correlations amongst the stock markets of the US, UK, Japan and Germany since the stock market
crash of 1987. Their study covers the period 1986-1988 and uses VAR techniques. King, Sentana and Wadhwani (1994) account for time variation in conditional covariances between stock markets using a multivariate factor model in which time variation in returns’ volatility is caused by changing volatility in market factors. They find evidence for time varying correlation structure among sixteen national markets.

The advent of multivariate GARCH models (Bollerslev, Engle and Wooldridge, 1988) has enabled researchers to explicitly specify conditional covariance and correlation equations and thus study their estimates over time. Longin and Solnik (1995) study correlation patterns of monthly excess returns for seven major countries over the period 1960-1990. Employing a multivariate GARCH model they conclude that the international covariances and correlation matrices are unstable over the period. Furthermore, they report that conditional correlations increase during periods of high volatility.

Ang and Bekaert (2002) apply a regime switching model in the context of international portfolio selection and find that anticipating a change of regime from a high-mean low-volatility regime to a low-mean high-volatility regime can improve investor utility. Engle and Colocito (2004) show that accounting for time varying correlations and asymmetries in correlations leads to lower portfolio risk.

Although a number of authors (e.g., Granger, 1986, Baillie and Bollerslev, 1989, and Hakkio and Rush, 1989) suggest that cointegration is not consistent with efficient markets, this is not necessarily the case, as shown in Dwyer and Wallace (1992). Kasa (1992) examines cointegration in the stock markets of the US, Japan, England, Germany and Canada and finds that the five markets are cointegrated and driven by one common trend. Kasa shows that cointegration tests yield much stronger results when applied to quarterly data than to monthly data and that the markets’ dividend yields are also cointegrated. Although the one common stochastic trend implies that in the long-run cross-country diversification benefits disappear, Kasa notes that it is the speed of adjustment coefficients that determine the persistence of deviations from the common trend and how relevant cointegration is
for diversification at any finite horizon. Further, Kasa demonstrates that national stock markets deviate from common trends for periods lasting several years and concludes that although the diversification benefits presented in other studies based on correlations of high frequency data are overstated, they do not entirely vanish for a finite horizon investor. Similarly Corhay, Rad and Urbain (1993) investigate cointegration among five major European stock markets on biweekly data over the period 1975-1991. They find that the stock markets of the UK, France, Germany and the Netherlands form a cointegrating vector, from which Italy is excluded. Byers and Peel (1993) note that even though international diversification gains may be limited when cointegration is present, they are not necessarily zero. This paper shows that gains depend on cointegrating coefficients, with smaller coefficients resulting in more gains. Byers and Peel study monthly stock market data for the US, the UK, Germany, Japan and the Netherlands covering the time frame October 1979 – October 1989 and find little evidence of cointegration. The exception is found in the UK – Japan pair. Given the low cointegrating coefficient between the two stock markets Byers and Peel conclude that gains from diversification across these two countries are not negligible. In a related study, Arshanapalli and Doukas (1993) show that the cointegrating relationship between daily stock market indices for the US, Japan, the UK, Germany and France has changed significantly since the stock market crash of October 1987. In the pre-October 1987 period there was no significant cointegration between the markets while in the post crash period there has been cointegration among the stock markets of the US, UK, Germany and France. The Japanese market appears to remain outside of the cointegration vector. Cashin, Kumar and McDermott (1995) also use cointegration and VAR methodology to measure the degree of international integration of industrial and emerging equity markets. They report that linkages have strengthened over time.

Richards (1995) challenges the results presented in Kasa (1992) largely due to the incorrect use of asymptotic critical values. He shows that once small-sample critical values are applied, the finding of cointegration between the national markets
reported in Kasa (1992) becomes invalid. In another study, Chan, Gup and Pan (1997) test cointegration across eighteen national stock markets spanning a time frame of more than 32 years, from January 1961 to December 1992. Using monthly data, they report only a small number of stock markets that show evidence of cointegration and conclude that international diversification arguments hold. Phylaktis and Ravazzolo (2005) examine linkages among a group of Pacific-Basin emerging stock markets and the US and Japan by estimating a multivariate cointegration model recursively over two sub-periods: 1980-1990 and 1990-1998. They investigate whether cointegration relationships are affected by the existence of foreign exchange restrictions and find that relaxation of these restrictions is not sufficient on its own to attract international investors and strengthen international market links but that other factors such as foreign ownership also play a role.

2.2. Lagged information transmissions in returns

Lagged return transmissions between national stock markets have also been investigated in a large number of studies. Most frequently the procedure involves statistical tests of leads and lags between two or more markets. Overall, evidence is in favour of the Efficient Market Hypothesis, with little or no return spillovers. While the early literature typically finds no statistically significant return spillovers, this view has largely changed in recent years. However, where returns spillovers are found they are typically of small magnitude and according to simulation studies would result in trading losses.

For example, Granger and Morgenstern (1970) find no evidence that would suggest the existence of statistically significant leads or lags when they apply spectral analysis to weekly stock market returns from eight countries. Similarly, Agmon (1972) reports no significant leads in monthly returns among the US, UK, German and Japanese stock indices. Branch (1974) arrives at the same conclusion in his study of 22 developed share markets. Hillard (1979) examines lead-lag relationships during the energy crisis of 1973 and 1974 and finds no discernable lagged movement.
transmissions either. Bertoneche (1979) reports some evidence that suggests existence of leads among weekly stock returns for seven European countries but insignificant lead-lag relationships between any of these countries and the US. In contrast, Schollhammer and Sand (1987) report that the US market generally leads other markets by one to two trading days. Their study includes 13 national share indices over the 1981–1983 period. Similarly, Eun and Shim (1989) note that between 1980 and 1985, most foreign markets lagged the US market by one to two days. Koch and Koch (1991) confirm this observation but conclude that most significant market adjustments among eight major stock markets are complete within 24 hours. They interpret their finding as evidence in support of international market efficiency. Cheung and Mak (1992) use weekly return time series for Asia-Pacific (emerging) markets and the US and Japanese (developed) markets to study return spillovers between 1977 and 1988. They find that the US market leads most of the Asian-Pacific emerging markets with the exceptions of three relatively closed markets (over that time period): Korea, Taiwan and Thailand.

Non-synchronous trading issues are considered by Becker, Finnerty and Tucker (1992). They point out that the US market has a strong effect on the Japanese market only during the first hour of trading in Japan, with subsequent hourly returns being independent of lagged US returns. Theodossiou and Lee (1993) examine the nature and degree of interdependence between the stock markets of the US, UK, Japan, Canada and Germany. They discover weak, yet statistically significant spillovers in the mean equations of weekly returns. The information is found to spill over from the US to the UK, Canada and Germany and from Japan to Germany. However, the spillovers account for a small per cent of the total variation in returns, typically less than six per cent. Frankel and Schmukler (1996) investigate how negative shocks in Mexican stocks transmit to Asia and Latin America and find that such shocks seem to have a stronger impact in countries with weak fundamentals. Similarly, Soydemir (2000) looks into transmission patterns of stock market movements between developed and emerging market economies by estimating a
VAR model on weekly returns. Although Eun and Shim (1994) argue that weekly time periods are too long to capture interactions that take place among stock markets, Soyemir shows that this is not the case for emerging markets. His impulse response functions suggest that spillovers have statistically significant impact for up to two weeks.

2.3. Lagged information transmissions in volatility

The idea of using volatility spillovers as a means for studying information transmission mechanisms was introduced following the stock market crash of October 19, 1987. The crash, which saw the Standard & Poor’s stock market index drop 20.4 percent had a domino effect across a large number of international markets. King and Wadhwani (1990) postulated a market “contagion” hypothesis in which they argued that stock prices in one country were influenced by changes in markets of other countries, beyond the levels that would be conceivable through economic fundamentals. They demonstrate that increases in volatility in one country can lead to of contagion, causing higher volatilities in other counties. A large number of empirical studies followed in their footsteps to test volatility spillovers between national stock markets. Some of these are reviewed below.

A majority of early volatility spillover studies were conducted on developed markets. For instance, short-run dependencies in volatility across three largest world stock markets are examined in Hamao, Masulis and Ng (1990). They find evidence of unidirectional volatility spillovers from the US to the UK and Japan and from the UK to Japan. Theodossiou and Lee (1993) report statistically significant volatility spillovers from the US market to the UK, Canada, Germany and Japan. Volatility is also found to transmit from the UK to Canada and from Germany to Japan. Lin, Engle and Ito (1994) investigate how returns and volatilities from the Tokyo and New York markets are related. Using intra-daily data they conclude that Tokyo daytime returns are correlated with New York overnight returns and the other way around.
More recently, investigations have been carried out to assess the spillover effects between developed and emerging markets and across emerging markets themselves. Wei, Liu, Yang and Chaung (1995) find volatility spillovers to both the Taiwanese and Hong Kong markets (emerging markets) from the US, UK and Japan (developed markets). Further, they report the Taiwanese market is more responsive to the price and volatility shocks from the developed markets than Hong Kong. Brailsford (1996) explores volatility spillovers between Australian and New Zealand equities. After accounting for the impact of overnight international news, as measured by the US market news, Brailsford finds significant volatility spillovers in both directions. However, it is not clear whether the volatility spillover from the New Zealand market is an artefact of international news that daily data is unable to fully isolate.

Geographic locality has also been a factor in volatility spillover investigations. The Bekaert and Harvey (1997) model distinguishes between local and global shocks and investigates volatility spillovers across emerging stock markets. Ng (2000) studies the magnitude and changing nature of volatility spillovers from Japan and the US to six Pacific-Basin equity markets. After accounting for the impact of the world factors as represented by the US market, she finds significant volatility spillovers from the region, represented by the Japanese market, to many of the Pacific-Basin countries. In a related study Miyakoshi (2003) documents additional evidence that Asian equity volatilities are influenced by both the US and Japanese volatility innovations. Further, a stronger effect is found to stem from Japan than from the US. Miyakoshi (2003) also reports statistically significant volatility spillovers from the Asian markets to Japan. Baele (2003) applies a volatility spillover model that breaks down volatility spillovers into country-specific, regional and world shock spillovers in thirteen European markets and the US. The model also allows for regime switches in volatility spillovers. Baele finds significant spillovers from both the regional and world level to national markets. The spillovers appear to have increased during the 1980s and 1990s and evidence suggests that the rise is more
pronounced for the regional (EU) spillovers. In a related study, Billio and Pelizzon (2003) conclude that volatility spillovers from both a world index and Germany increased after EMU in most European stock markets.

2.4. Asymmetric Effects

Asymmetric responses were first reported in volatility by Black (1976) and Christie (1982) and currently there are two explanations for the tendency of equity volatility to increase more following a negative return shock than after a positive shock of the same magnitude. Under the leverage effect theory (Black, 1976 and Christie, 1982) a negative stock price shock will increase a firm’s debt to equity ratio, making the stock riskier and therefore raising volatility. A related hypothesis, the volatility feedback theory, (e.g., Campbell and Hentschel, 1992; Bekaert and Wu, 2000; and Wu, 2001) asserts that if stock volatility is priced, then an anticipated increase in volatility causes stock prices to rise and causes returns to fall.

Asymmetric effects have also been found in correlations and relate to the observation that links between financial markets strengthen during bear markets. Early studies report asymmetries in covariances using constant correlation models (e.g., Kaplanis, 1988; Koutmos and Booth, 1995; Koutmos, 1996; and Scruggs, 1998) while more recent studies report asymmetries in time varying correlations (e.g., Kroner and Ng, 1998; and Cappiello, Engle and Sheppard, 2003). Thus asymmetries are important and not accounting for them can lead to incomplete descriptions of the conditional second moment matrix.

3. Econometric Specification

The conditional mean of the differenced log price (i.e. returns) series is specified as a vector error correction model:

\[ \Delta P_t = \mathbf{c} + \Pi \Delta P_{t-1} + \sum_{j=1}^{k} \phi_j \Delta P_{t-j} + \mathbf{u}_t \]  

(1)
where $P_t = \begin{bmatrix} P_{1t}, P_{2t}, P_{3t}, P_{4t} \end{bmatrix}'$ is a vector of I(1) log prices, $\mathbf{c}$ is a $(4 \times 1)$ vector of constants, $\mathbf{\phi}_i$ are $(4 \times 4)$ autoregressive coefficient matrices, while $\mathbf{\Pi}$ is a $(4 \times 4)$ matrix whose rank determines the number of cointegrating vectors of the system. The ordering of the markets within the system is irrelevant as this is a reduced form specification. There are three possibilities regarding the rank $\mathbf{\Pi}$. If the rank is zero, then there is no linear relationship of the variables that is stationary and the VECM reduces to a VAR in first differences. If $\mathbf{\Pi}$ is of full rank $n$, where $n$ is the number of variables (4 in this case) all of the variables are stationary and thus cannot be I(1). In other cases where the rank of $\mathbf{\Pi}$ is greater than zero but less than $n$ ($0 < r < n$) there are $r$ cointegrating vectors and $n - r$ stochastic trends in the system. In this case it is possible to define $\mathbf{\Pi} = \mathbf{a}\mathbf{\beta}'$ where $\mathbf{a}$ and $\mathbf{\beta}$ are of dimension $(n \times r)$ and $\mathbf{\beta}$ is a matrix of cointegrating parameters that consists of $r$ cointegrating column vectors while $\mathbf{a}$ can be interpreted as a matrix of speed of adjustment coefficients. The speed of adjustment coefficients tell us how quickly dependent variables adjust to deviations from the long run equilibrium. The model can thus be rewritten as:

$$\Delta P_t = \mathbf{c} + \mathbf{a}(\mathbf{\beta}'P_{t-1}) + \sum_{i=1}^{A} \mathbf{\phi}_i \Delta P_{t-i} + \mathbf{u}_t.$$  \hfill (2)

The vector of innovations $\mathbf{u}_t$, conditional on the information set $\Psi_{t-1}$ is assumed to be conditionally Normal:

$$\mathbf{u}_t | \Psi_{t-1} \sim N(\mathbf{0}, \mathbf{H}_t).$$  \hfill (3)

Further, the conditional variance matrix $\mathbf{H}_t$ can decomposed as:

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t$$  \hfill (4)

Following Engle (2002) $\mathbf{D}_t$ is specified as a diagonal matrix of time varying standard deviations of dimension $(n \times n)$ while $\mathbf{R}_t$ is defined as a symmetric matrix of conditional correlation coefficients whose elements are pair-wise conditional
correlations $\rho_{ij,t}$. The conditional covariance matrix can thus be written in the following way:

$$
\mathbf{H}_t = \begin{bmatrix}
  h_{1t} & \cdots & h_{nt}
  \\
  \vdots & \ddots & \vdots \\
  h_{nt} & \cdots & h_{nt}
\end{bmatrix} = \begin{bmatrix}
  h_{1t} & \cdots & \rho_{nt}\sqrt{h_{1t}h_{nt}}
  \\
  \vdots & \ddots & \vdots \\
  \rho_{nt}\sqrt{h_{nt}h_{1t}} & \cdots & h_{nt}
\end{bmatrix}
$$

(5)

Diagonal elements of $\mathbf{H}_t$, the conditional variances, whose square roots are elements of $\mathbf{D}_t$ are specified as augmented GJR (1,1,1) models. The augmentation is accomplished with volatility spillover terms and their asymmetric counterparts. The conditional variance equations can be written as:

$$
h_{i,j,t} = \sigma_i + \beta_i h_{i,j,t-1} + \sum_{j=1}^{4} (\alpha_i + \delta_i I_{i,t-1}) u_{i,j,t-1}^2
$$

(6)

where $I_{i,t} = \begin{cases} 
1 & u_{i,t} < 0 \\
0 & u_{i,t} \geq 0 
\end{cases}$.

Each variance is dependent on its own past, the previous period’s volatility shocks (spillovers) from all four markets and asymmetric volatility spillovers associated with negative news.

The ADCC model specifies the correlation matrix $\mathbf{R}_t$ in the following way: Standardised innovations $\varepsilon_i$ can be obtained by dividing market innovations $u_{i,t}$ by their conditional standard errors $\varepsilon_i = \frac{u_{i,t}}{\sqrt{h_{i,t}}}$ or $\varepsilon_i = \mathbf{D}^t \mathbf{u}_i$. The standardised innovations $\varepsilon_i$ are then assumed to be conditionally Normal themselves ($\varepsilon_i \sim N(\mathbf{0}, \mathbf{R}_t)$). Further, the covariance matrix of the standardised residuals is identical to the correlation matrix due to the fact that its standard deviations are one. This can be better seen by considering the relationship between the covariance and correlation below:
If both elements in the denominator are equal to one, the two are identical. The last step is to specify the form of $R_t$. I specify this in a general form proposed by Cappiello, Engle and Sheppard (2004):
\[
R_t = \text{diag}\{Q_t\}^{-1} Q_t \text{diag}\{Q_t\}^{-1}
\]
where
\[
Q_t = (\tilde{Q} - A'Q_tA - B'	ilde{Q}B - G'	ilde{N}G) + A'\tilde{e}_{t-1}A + B'Q_{t-1}B + G'\eta_{t-1}\eta_{t-1}G.
\]
In this application, I choose a more parsimonious scalar specification of $A$, $B$ and $G$ matrices so that the model simplifies to:
\[
Q_t = \tilde{Q}(1 - a - b) - g\tilde{N} + a\tilde{e}_{t-1} + bQ_{t-1} + g\eta_{t-1}\eta_{t-1}
\]
where $\eta_t = I[\epsilon_t < 0] \circ \epsilon_t$ isolates volatility shocks associated with negative return innovations. I also calculate $Q_t = \frac{1}{T} \sum_{t=1}^{T} \epsilon_t \epsilon_t'$ and $\tilde{N} = \frac{1}{T} \sum_{t=1}^{T} \eta_t \eta_t'$ to implement variance targeting.

The model is estimated in two steps where a VECM is specified and estimated for the return series first and then an ADCC fitted to estimated residuals. Identification of the lag length $p$ in VECM is achieved through estimation of a VAR on the series in levels and using model selection criteria to ascertain the appropriate lag length. The length used in VECM is then $p^* = p - 1$; that is, one lag less than the VAR lag length. The appropriate lag length $p^* = 2$ was chosen by the AIC and FP model selection criteria.

After having estimated the VECM and de-meaned the return series, the estimation of the ADCC is based on the assumption that the residuals $u_t$ are conditionally normally distributed (i.e., $u_t | \Psi_{t-1} \sim N(0, H_t)$).
Although a two step estimation (Engle, 2002) is possible and yields consistent estimates they are inefficient. In this paper, I perform the estimation of ADCC in one step, jointly maximizing volatility and correlation parameters in order to achieve efficient estimates.

Even though I assume the standardized residuals to be normally distributed, a violation of this assumption does not invalidate estimated coefficients because the quasi-maximum likelihood arguments apply as long as the conditional mean and variance equations are correctly specified (Hamilton, 1994, p.126). In this case Bollerslev-Wooldridge (1992) standard errors give optimal estimates.

4. Data Summary and Preliminary Statistical Analysis

The dataset used in this paper consists of four weekly time series for the following national stock market indices: Standard and Poor’s 500 (the US), Nikkei Stock Average (Japan), FTSE All Share Index (the UK) and All Ordinaries Share Index (Australia). The sample period is 26 November 1971 to 1 April 2005 and contains 1,741 weekly price observations. The data was obtained from DataStream® in common (USD) currency and the weekly frequency was chosen to circumvent problems associated with non-synchronous data identified by Burns, Engle and Mezrich (1998) and Martens and Poon (2001).3

Figure 1 presents a time series graph of the indices in log levels and returns.

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3 Briefly, estimating second conditional moments on non-synchronous data leads to underestimation of conditional correlations/covariance and inability to distinguish between contemporaneous correlations and lagged spillover effects.
Figure 1: National stock market indices in returns and (log) levels.

Top graph depicts returns whereas the lower portion of the figure illustrates indices in log levels. A different constant has been added to each of the return series in order to present them in one graph. This does not affect variability of the series.

Even though the series look nonstationary in levels, they seem to move in a loose unison. This observation is typically associated with the statistical concept of cointegration (Engle and Granger, 1987) where a linear combination(s) of nonstationary variables exists that produces a stationary process(es).

As the graph indicates, the returns are consistent with frequently cited stylized facts such as the existence of large outliers, synchronicity of extreme observations and volatility clustering. Volatility clusters are usually associated with time-varying conditional volatility processes such as GARCH (Bollerslev, 1986). The outliers are typically of negative sign such as the ones associated with the stock market crash of October 1987 and more recently the terrorist attacks of September 11, 2001. Although, it may be tempting to try to account for the outliers using dummy variables in the mean equations, I do not do so for the following reason. In
financial applications such as asset allocation and risk management, we use forecasts of the conditional covariance matrix rather than in-sample estimate to make decisions. As my aim here is to characterise interdependencies between national stock markets and comment on their implications for financial decisions, eliminating outliers through dummy variables and then making statements about the conditional covariance matrix that has been estimated on the residuals would be misleading. It is unrealistic to assume that one can forecast outliers, and a covariance matrix that has been estimated on residuals containing no outliers will typically imply a lower level of uncertainty than there really is.

Summary statistics for the returns are presented in Table 1.

**Table 1: National stock markets' summary statistics.**

<table>
<thead>
<tr>
<th></th>
<th>US</th>
<th>Japan</th>
<th>UK</th>
<th>Australia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.15</td>
<td>0.16</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>2.20</td>
<td>2.97</td>
<td>2.86</td>
<td>2.92</td>
</tr>
<tr>
<td>Reward-Risk Ratio</td>
<td>0.07</td>
<td>0.05</td>
<td>0.05</td>
<td>0.04</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.37</td>
<td>0.06</td>
<td>-0.20</td>
<td>-1.66</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>6.24</td>
<td>5.19</td>
<td>9.27</td>
<td>22.94</td>
</tr>
<tr>
<td>Jarque-Bera p-value</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Jarque-Bera statistic</td>
<td>799.53</td>
<td>349.84</td>
<td>2866.34</td>
<td>29645.40</td>
</tr>
</tbody>
</table>

Summary statistics are calculated on weekly log returns \( r_t = \ln(P_t/P_{t-1}) \times 100 \) over the period November 1971 - April 2005. Reward-Risk ratio is the mean to standard deviation ratio.

Over the sample period from November 1971 to April 2005, the S&P 500 clearly outperformed the other three indices on a risk adjusted basis, as indicated by Reward-Risk ratios. On the other end of the spectrum, the Australian All Ordinaries index recorded the lowest mean return while displaying a relatively high level of risk compared with the other markets. All five indices showed departures from unconditional normality with excess skewness and kurtosis, and large Jarque-Bera statistics with p-values being equal to zero to three decimal places. This is especially true for the Australian market, which exhibited the largest Jarque-Bera statistic, most likely due to its 34.36% drop during the week of the October 1987 stock market crash. Next, Table 2 presents the unconditional correlation coefficients.
Table 2: Correlation Matrix of the National Stock Markets Returns.

<table>
<thead>
<tr>
<th></th>
<th>US</th>
<th>Japan</th>
<th>UK</th>
<th>Australia</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>1.00</td>
<td>0.239</td>
<td>0.395</td>
<td>0.279</td>
</tr>
<tr>
<td>Japan</td>
<td>1.00</td>
<td>1.000</td>
<td>0.287</td>
<td>0.295</td>
</tr>
<tr>
<td>UK</td>
<td>1.00</td>
<td>1.000</td>
<td>0.358</td>
<td></td>
</tr>
<tr>
<td>Australia</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Unconditional correlations are calculated on weekly log-returns \( r_t = \ln \left( \frac{P_t}{P_{t-1}} \right) \times 100 \) for the period November 1971 - April 2005.

The weekly correlation seems to be greatest for the US-UK pair while the smallest is recorded between the two largest markets, the US and Japan.

4.1. Unit Root Tests

As previously mentioned and illustrated in Figure 1, the log-return series exhibit nonstationary behaviour. In order to identify the degree of integration, I perform Augmented Dickey-Fuller (1979) and Phillips-Perron (1988) tests. Both of these procedures test the null hypothesis of a unit root in the autoregressive representation of the series. The Augmented Dickey-Fuller (ADF) test constructs a parametric correction for higher-order autocorrelations by assuming that the series follows an AR\( (p) \) process and adding lagged difference terms of the dependent variable to the test regression. Rejecting the null hypothesis implies that the series is stationary. The number of lagged difference terms \( p \) is determined using the Schwartz Information Criterion. The Phillips-Perron test differs from the ADF test in that it accounts for autocorrelation non-parametrically and modifies the t-ratio of the \( \gamma \) coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. A linear time trend and a drift were included in both tests that are reported in Table 3. The findings however did not change upon sequential exclusion of the nuisance parameters.
Table 3: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests.

<table>
<thead>
<tr>
<th></th>
<th>Levels</th>
<th>First Differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ADF</td>
<td>PP</td>
</tr>
<tr>
<td>US</td>
<td>-2.28</td>
<td>-2.30</td>
</tr>
<tr>
<td>Japan</td>
<td>-1.16</td>
<td>-1.14</td>
</tr>
<tr>
<td>UK</td>
<td>-2.71</td>
<td>-2.60</td>
</tr>
<tr>
<td>Australia</td>
<td>-3.22</td>
<td>-3.25</td>
</tr>
</tbody>
</table>

Levels refer to natural logarithms of variables so that the first differences are approximately percentage returns. Unit root tests are performed over the period November 1971 - April 2005. 1% critical value for all tests is -3.968, 5% critical value is -3.415. * denotes significance at 5%, ** significance at 1%. The tests are estimated with a drift and a linear trend; however, the findings do not change upon exclusion of these variables.

Thus, all variables appear to be $I(1)$ processes in log-levels and stationary in returns (first differences).

4.2. **Cointegration Tests**

Next, I examine whether the national stock markets are cointegrated using Johansen (1988, 1991) tests. The tests are performed by calculating eigenvalues of the $\Pi$ matrix in Equation (1) and computing two related statistics: the Eigenvalue Trace statistic and the Maximum Eigenvalue statistic. Noting that the cointegration rank, which is the number of cointegration vectors, is equal to the number of non-zero eigenvalues of the matrix $\Pi$, the two statistics test similar hypotheses. While the Eigenvalue Trace statistic tests the null hypothesis that the number of distinct cointegration vectors is less than or equal to some number $k$ against a general alternative hypothesis, the Maximum Eigenvalue statistic tests the same null against the alternative of $k+1$ cointegrating vectors. In practical applications two additional variables need to be specified. The first is the number of lags in the VECM model. In this paper, I follow Richards’ (1995) suggestion regarding the lag length selection criteria and choose the optimal lag length of 2 ($p = 2$) for the VECM based on the information selection criteria given in Table A.2. Further, one must also decide whether to include an intercept and/or trend in the cointegrating equation(s) and/or VECM outside the cointegrating equation. The results presented below in Table 4 are based on a model that includes an intercept in the cointegrating vector and a drift in
the VECM outside the long-run relationship. However, the findings are not sensitive to the exclusion of either one or both of the intercepts.

Table 4: Cointegration rank tests.

<table>
<thead>
<tr>
<th>Hypothesized No. of CE(s)</th>
<th>Trace Statistic</th>
<th>5 Percent Critical Value</th>
<th>1 Percent Critical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>None *</td>
<td>50.73*</td>
<td>47.21*</td>
<td>54.46*</td>
</tr>
<tr>
<td>At most 1</td>
<td>21.59</td>
<td>29.68</td>
<td>35.65</td>
</tr>
<tr>
<td>At most 2</td>
<td>8.79</td>
<td>15.41</td>
<td>20.04</td>
</tr>
<tr>
<td>At most 3</td>
<td>2.45</td>
<td>3.76</td>
<td>6.65</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hypothesized No. of CE(s)</th>
<th>Max-Eigenvalue Statistic</th>
<th>5 Percent Critical Value</th>
<th>1 Percent Critical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>None *</td>
<td>29.14*</td>
<td>27.07*</td>
<td>32.24*</td>
</tr>
<tr>
<td>At most 1</td>
<td>12.80</td>
<td>20.97</td>
<td>25.52</td>
</tr>
<tr>
<td>At most 2</td>
<td>6.34</td>
<td>14.07</td>
<td>18.63</td>
</tr>
<tr>
<td>At most 3</td>
<td>2.45</td>
<td>3.76</td>
<td>6.65</td>
</tr>
</tbody>
</table>

Cointegration tests are performed on log weekly returns over the period November 1971 – April 2005. Trace test indicates 1 cointegrating equation(s) at the 5% level. Max-Eigenvalue test indicates 1 cointegrating equation(s) at the 5% level. * denotes rejection of the hypothesis at the 5% level. The critical values are taken from Osterwald-Lenum (1992).

As the results indicate, each test rejects the null hypothesis of “no cointegration” at the 5 per cent level but fails to reject the null of “at most 1 cointegrating vector”. I therefore conclude this section noting that the four national markets are nonstationary but cointegrated with one cointegration vector or, alternatively, three common stochastic trends.

5. **Empirical Findings**

Table 5 presents the vector error correction model estimates. The speed of adjustment coefficients are all statistically significant at the 10 per cent level although the UK coefficient is insignificant at the 5 per cent level.
Table 5: VECM estimates.

<table>
<thead>
<tr>
<th></th>
<th>USₜ</th>
<th>JPₜ</th>
<th>UKₜ</th>
<th>AUₜ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const. Coef.</td>
<td>-0.12</td>
<td>-0.53</td>
<td>-0.23</td>
<td>1.00</td>
</tr>
<tr>
<td>t-stat</td>
<td>-6.27</td>
<td>-4.63</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>VECM Coef.</td>
<td>-0.45</td>
<td>-2.96</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>ΔUSₜ Coef.</td>
<td>-0.09</td>
<td>0.46</td>
<td>0.00</td>
<td>0.14</td>
</tr>
<tr>
<td>p-value</td>
<td>0.01</td>
<td>0.02</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>ΔJPₜ Coef.</td>
<td>-0.01</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>p-value</td>
<td>0.01</td>
<td>0.01</td>
<td>0.07</td>
<td>0.07</td>
</tr>
<tr>
<td>ΔUKₜ Coef.</td>
<td>0.08</td>
<td>-0.01</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>p-value</td>
<td>0.01</td>
<td>0.01</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>ΔAUₜ Coef.</td>
<td>-0.01</td>
<td>0.46</td>
<td>0.00</td>
<td>0.14</td>
</tr>
<tr>
<td>p-value</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Diagnostic Tests

<table>
<thead>
<tr>
<th></th>
<th>Jarque-Bera</th>
<th>J.B. p-value</th>
<th>Q-Stat (20)</th>
<th>Q-Stat (20) p-value</th>
<th>Q-Stat – squared residuals (20)</th>
<th>Q-Stat – squared residuals (20) p-value</th>
<th>LM ARCH(5)</th>
<th>LM p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const.</td>
<td>808.4</td>
<td>0.00</td>
<td>7.30</td>
<td>0.20</td>
<td>288.3</td>
<td>0.00</td>
<td>122.7</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>344.6</td>
<td>0.00</td>
<td>19.54</td>
<td>0.49</td>
<td>274.6</td>
<td>0.48</td>
<td>100.0</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>2214.6</td>
<td>0.00</td>
<td>19.62</td>
<td>0.48</td>
<td>329.2</td>
<td>0.46</td>
<td>113.9</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>19435.8</td>
<td>0.00</td>
<td>19.96</td>
<td>0.46</td>
<td>99.9</td>
<td>0.00</td>
<td>52.5</td>
<td>0.00</td>
</tr>
</tbody>
</table>

The model is estimated on weekly returns over the period November 1971 – April 2005, t-ratios are given in parenthesis. Grey areas point out rejection of null at a level smaller than 10%. Cointegrating vector is normalized on the UK market coefficient.

The coefficients are of largest magnitude in the Japanese and Australian equations, although low with adjustments to deviations from the long-run equilibrium of about 1.4 per cent per week. The UK coefficient is of smallest magnitude. All speed of adjustment coefficients are of the right sign.
Other coefficients typically statistically significant in each equation are the ones on the lagged dependent variable term. Further, the US and the UK markets appear to exhibit some bidirectional short run return spillovers, whereas the Australian equities are affected in the short-run by both the US and UK lagged returns.

Overall, the explanatory power of the VECM model is relatively weak. In the US and UK equations, only 2 per cent of the total variation in returns is explained by the model. Similar figures are recorded for Japan, with about 3 per cent of variability explained and for Australia, which has the highest R-squared of 6 per cent. Although the Jarque-Bera statistics indicate non-Normality in estimated residuals, the Ljung-Box Q statistics (for up to 20 lags) suggest that the VECM filters out autocorrelation quite well, with the p-values being in excess of 20 per cent. The autocorrelation however remains present in squared residuals as indicated by high Q-statistics computed from squared residuals with p-values equal to zero to two decimal places. As the presence of autocorrelation in squared residuals is typically associated with time-varying conditional volatility I also report estimated LM ARCH tests (Engle, 1982). The tests confirm existence of ARCH type behaviour in the residuals and this is modelled next in the ADCC framework.

5.1. Conditional Volatility, Correlations and Volatility Spillovers
As illustrated in the Table 6 below, all conditional variance equations exhibit asymmetric behaviour associated with negative news shocks. The asymmetric effect is of greatest magnitude (relative to positive news) in Australia and smallest in the UK.
Table 6: Conditional second moment matrix parameter estimates.

<table>
<thead>
<tr>
<th>Volatility Equation for:</th>
<th>US</th>
<th>Japan</th>
<th>UK</th>
<th>Australia</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coef.</td>
<td>p-value</td>
<td>coef.</td>
<td>p-value</td>
</tr>
<tr>
<td>Volatility Spillover</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>From:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>US</td>
<td>-</td>
<td>0.046</td>
<td>0.03</td>
<td>0.001</td>
</tr>
<tr>
<td>US (Asym.)</td>
<td>-</td>
<td>-0.003</td>
<td>0.94</td>
<td>0.077</td>
</tr>
<tr>
<td>Japan</td>
<td>0.005</td>
<td>0.40</td>
<td>-</td>
<td>-0.002</td>
</tr>
<tr>
<td>Japan (Asym.)</td>
<td>-0.011</td>
<td>0.12</td>
<td>-</td>
<td>-0.003</td>
</tr>
<tr>
<td>UK</td>
<td>-0.008</td>
<td>0.01</td>
<td>-0.009</td>
<td>0.28</td>
</tr>
<tr>
<td>UK (Asym.)</td>
<td>0.020</td>
<td>0.02</td>
<td>0.001</td>
<td>0.96</td>
</tr>
<tr>
<td>Australia</td>
<td>0.005</td>
<td>0.60</td>
<td>0.001</td>
<td>0.98</td>
</tr>
<tr>
<td>Australia (Asym.)</td>
<td>-0.005</td>
<td>0.66</td>
<td>0.002</td>
<td>0.97</td>
</tr>
<tr>
<td>GJR(1,1,1) Parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>α (Arch)</td>
<td>0.036</td>
<td>0.02</td>
<td>0.054</td>
<td>0.00</td>
</tr>
<tr>
<td>δ (Asym. Arch)</td>
<td>0.116</td>
<td>0.00</td>
<td>0.141</td>
<td>0.00</td>
</tr>
<tr>
<td>β (Garch)</td>
<td>0.850</td>
<td>0.00</td>
<td>0.801</td>
<td>0.00</td>
</tr>
<tr>
<td>Correlation Parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>a</td>
<td>0.009</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>g</td>
<td>0.987</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b (Asym.)</td>
<td>0.003</td>
<td>0.06</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The model is estimated on weekly returns over the period November 1971 – April 2005. Grey areas point out p-values smaller than 10%. P-values are calculated using Bollerslev-Wooldridge (1992) robust standard errors.

Bidirectional volatility spillovers are recorded between the US and UK. While the US transmits volatility to the UK only when the volatility shock is associated with bad news in the US, the UK spillover to the US does not depend on the sign of the shock. Interestingly, the UK volatility transmission to the US, when related to positive news in the UK is negative, that is, it decreases volatility in the US on average.

The US also transmits volatility to Japan with the volatility shocks being of the same magnitude for positive and negative news. Lastly, Australia receives volatility spillovers from the US but only when related to negative news in the US.
The conditional correlation equation parameters are given in the lower portion of Table 6. The coefficients sum to just below one indicating a high level of persistence in conditional correlations. This is confirmed with fitted conditional correlation series presented in figures 2 - 4 below.

**Figure 2: Estimated weekly conditional correlations (US-AU, UK-AU).**

We can make three observations from the above graph, two of which we can also make for the other market pairs. First, in accord with the asymmetric component of the conditional correlation equation, which is statistically significant at the 10 per cent level, the correlations are higher during periods of large negative shocks. Three such periods can be readily identified: the oil price shocks of 1973-1994, the stock market crash of 1987 and more recently, although not of the same magnitude, the 11/9/2001 terror attacks. This asymmetric effect in conditional correlations is illustrated more clearly using a news impact curve in Figure A.1 of the Appendix.

Another feature exhibited in all six conditional correlation series is a half-cycle starting in 1979 and finishing in 1987, with peaks between 1982 and 1984. There was also an upward trend in conditional correlations between the US and Australia and the UK and Australia over the periods 1989-2002 and 1993-2002 respectively. Both of these correlations have however since stabilized.
As Figure 3 illustrates, conditional correlations for the US-Japan and UK-Japan market pairs display no such trends. In fact, both of these correlations are below their all time highs recorded in 1982 and 1992, respectively, and have followed similar paths over the entire sample.

Figure 3: Estimated weekly conditional correlations (US-JP, UK-JP).

Conditional correlations between the remaining two market pairs: US-UK and Japan-Australia are presented in Figure 4. Like the other two correlation series involving Japan, the Japan-Australia series exhibits no sustained long-term pattern. On the other hand, the US-UK pair shows an upward trend over the period 1993-2002. More recently, from 2002 to 2005 this correlation seems to have stabilized and has started to decline.
5.2. Effects of Asymmetric Responses to Bad News

All conditional volatilities and correlations exhibit asymmetric responses to bad news as illustrated in Table 6. Volatility spillovers to the UK and Australia are also asymmetric while the UK volatility spillover to the US has an asymmetric component. In this section, I illustrate interactions of conditional correlations and volatility due to these asymmetries and consider their implications for portfolio risk management.

Consider a portfolio made up of \( N \) assets, where \( w_i \) is the portfolio weight of asset \( i \) and \( \sum_{i=1}^{N} w_i = 1 \). Then, the portfolio variance is given by:

\[
\sigma_{pt}^2 = \sum_{i=1}^{N} w_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \rho_{ij}\left[\sigma_i^2 \sigma_j^2\right]^{1/2}
\]

The above equation tells us that as the number of assets increases, the proportion of portfolio variance due to individual asset variances gets smaller while the exposure to
covariances between the assets, that is, the interaction between volatility and correlation, becomes greater. Given the estimated second moment equations (Table 6), it is clear that the relationship between any two markets’ volatility and correlation strengthens when bad news hits the two markets at the same time. This causes covariances to increase and results in reduction of diversification gains and increased portfolio risk. A relevant question to ask is then ‘how much does the link between correlations and volatility increase during bear markets’? Table 7 presents correlations between estimated conditional volatility and correlation series for each market pair calculated over two sub-samples, one that consists only of periods of major crises and one that contains the remainder of the sample.

Table 5.7: Correlations between realised conditional variances and realised conditional correlations.

<table>
<thead>
<tr>
<th></th>
<th>$h_{us}$</th>
<th>$h_{jp}$</th>
<th>$h_{uk}$</th>
<th>$h_{au}$</th>
<th>$\rho_{us-jp}$</th>
<th>$\rho_{jp-uk}$</th>
<th>$\rho_{jp-au}$</th>
<th>$\rho_{fp-uk}$</th>
<th>$\rho_{fp-au}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_{us}$</td>
<td>1.00</td>
<td>0.32</td>
<td>-0.01</td>
<td>1.00</td>
<td>0.05</td>
<td>0.17</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$h_{jp}$</td>
<td>0.90</td>
<td>1.00</td>
<td>0.10</td>
<td>1.00</td>
<td>0.96</td>
<td>1.00</td>
<td>-0.18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho_{us-jp}$</td>
<td>0.33</td>
<td>0.21</td>
<td>1.00</td>
<td>0.58</td>
<td>0.61</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$h_{uk}$</td>
<td>1.00</td>
<td>0.60</td>
<td>0.22</td>
<td>1.00</td>
<td>0.12</td>
<td>0.10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$h_{au}$</td>
<td>0.95</td>
<td>1.00</td>
<td>-0.05</td>
<td>0.95</td>
<td>1.00</td>
<td>-0.18</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho_{us-uk}$</td>
<td>0.36</td>
<td>0.29</td>
<td>1.00</td>
<td>0.51</td>
<td>0.63</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$h_{au}$</td>
<td>1.00</td>
<td>0.69</td>
<td>0.07</td>
<td>1.00</td>
<td>0.89</td>
<td>-0.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho_{us-au}$</td>
<td>0.38</td>
<td>0.23</td>
<td>1.00</td>
<td>0.37</td>
<td>0.47</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Correlations between estimated conditional variances and correlations computed over periods of financial crisis are given in lower triangles, while correlations calculated over the remainder of the data sample are presented in upper triangles. The crises considered are: 17/10/1973 – 17/03/1974 Oil price shock, 17/10/1987 – 4/12/1987 stock market crash, 19/12/1994 – 31/12/1994 Mexican Peso Crisis and 7/9/2001 – 12/10/2001 September 11, 2001, terrorist attacks. The crisis sub-sample consists of 29 weekly observations; the remainder of the sample contains 1712 observations.

All market pairs share a similar pattern where elements in the lower triangles (estimated over the crises periods) are larger than their counterparts in the upper triangles (estimates calculated over the remainder of the sample). Correlations between any two estimated weekly volatilities increase up to eighteen times during periods of financial distress, while a large majority of correlations between estimated volatility and conditional correlation series turns from weakly negative to moderately positive. These dramatic changes brought on by global negative news shocks highlight the effect of asymmetric responses that have been frequently cited in the literature (e.g., Cappiello, Engle and Sheppard, 2004; and Ang and Bekaert, 2002).

6 Conclusion

Time series dependences are measured among the national stock markets of the US, UK, Japan and Australia using long-run cointegration, conditional correlations and volatility spillovers over the period 26 November 1971 to 1 April 2005.

I find that the four markets are cointegrated with one vector but adjust to deviations from the long-run equilibrium relatively slowly, taking between 1 ½ years in Japan and Australia and 2 ½ in the UK. The explanatory power of the VECM on weekly returns is small, from 2 per cent for the US market to 6 per cent for the Australian market. An implication of these findings is that cointegration is unlikely to diminish diversification benefits over shorter investment horizons, although it can have a significant effect over longer periods.

In the conditional second moment matrix, I find asymmetric responses to negative news in volatilities, correlations and volatility spillovers and illustrate their

4 The dates for the Mexican Peso crisis and the stock market crash were adopted from Forbes and Rigobon (2002).
effect over several periods of stock market crises. Bidirectional volatility spillovers are found between the US and UK and unidirectional transfers from the US to the other markets. The spillovers to Australia and UK are statistically significant at 5 per cent only when related to bad news in the US, while the spillover to Japan is not dependent on the sign of the US news. Weekly conditional correlations exhibit time varying behaviour and some common features. The Australian stock market has experienced an upward trend in correlation with the US and UK over the periods of 1989-2002 and 1993-2002, respectively, while the US-UK market pair co-movement strengthened between 1993 and 2003. These correlations have since stabilised. Conditional correlations involving Japan show no sustained longer term pattern although they follow similar paths.

In order to measure the effects of the dependencies uncovered here I estimate correlations between any two realised variance/correlations series and show that these increase for most of the realised variance/correlation pairs during periods of financial crises. The largest increase of eighteen times is recorded between the realised variances of the UK and Japan. Similarly the correlation between the UK volatility and the Japan-UK conditional correlation rises from -18 per cent to 61 per cent.

The above reported effects of asymmetries coupled with the finding of cointegration among national stock markets reported here suggests that common negative shocks can be regarded as a regularity rather than as an aberration. This emphasises the importance of taking the asymmetries into account when constructing risk management tools and policies. Failing to do so can result in inefficient covariance matrix forecasts, suboptimal investment decisions and underestimation of risk.
Appendix

Figure A.1: Conditional correlation news impact surface.

According to the scaler version of the ADCC model, Eq. (5.10), the conditional pair wise correlations between the national stock markets indices of the US, UK, Japan and Australia are driven by the same persistence parameters. Thus I calculate only one News Impact Surface to demonstrate the effect of the asymmetric term in all correlations. The news impact surface is scaled to correspond to the average correlation coefficient between the four countries.
References:


