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Temporal links between the Asia-Pacific and international stock markets: 1971-2010

Abstract

I examine interdependencies between the national stock markets of the US, the UK, Japan and Australia, and consider their implications for international portfolio diversification over the 1971-2010 time period. It appears that the risk-reduction benefits associated with diversification across the Anglo-American markets have steadily declined since 1993, while the diversification gains of investing in Japanese equities began diminishing around 2001, when the correlations between Japan and the other three markets commenced an upward trend. Like volatility, all conditional correlations increase in magnitude when associated with bear markets. It seems that international diversification fails to provide risk-protection when it is needed the most, during periods of financial distress.

Keywords: stock market interdependencies, Asia-Pacific region, VECM, MGARCH, portfolio risk.
JEL Classification: G15, G11, C32.

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 thus decrease the benefits of international diversification (e.g., Longin and Solnik, 1995; Koutmos and Booth, 1995; Billio and Pelizzon, 2003). In the light of these arguments, 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, over the 26 November 1971 – 9 April 2010 time period.

The empirical method used here comprises several econometric time-series techniques. The price process is characterized by a vector error correction model (VECM), conditional volatilities are modeled using a GJR GARCH (generalized autoregressive conditional heteroskedasticity) specification of Glosten, Jagannathan and Runkle (1993), and the conditional correlation matrix is described with a generalized dynamic conditional correlation (ADCC) specification of Cappiello, Engle and Sheppard (2006). The asymmetric effects associated with negative news shocks, i.e. volatility increases more when associated with bad news first reported by Black (1976) and Christie (1982), are modeled in all components of the second moment matrix, including the correlations and volatility spillovers. I estimate the model on weekly stock market index returns denominated in US dollars.

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 the VECM model for weekly returns is small, ranging between 2 percent for the US and the UK, and 5 percent for the Australian market. Although the Australian market adjusts most rapidly to deviations from the long-run equilibrium, it does so at a rate of about 1.3 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 short-to-medium holding periods. However, as pointed out by Philaktis and Ravazzolo (2005) and Kasa (1992) the long-run relationship can reduce diversification gains over longer holding periods.

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. I find bidirectional volatility spillovers between the US and the UK, and interestingly between Australia and Japan. The spillovers to Australia and the UK are statistically significant only when related to bad news in Japan and the US respectively, while an additional spillover from the US to Japan is insensitive to the sign of the US news shock. These findings indicate that a portion of each country's market risk is due to lagged transmissions of international risk and is thus, to a certain degree, predictable. Further, conditional correlations are also found to exhibit time varying behavior and asymmetric responses to negative news. The correlations between the US, the UK and Australia display an upward trend that starts around 1993. On the other hand, the conditional correlation coefficients that include Japan remained relatively steady until the end of 2001, when they also assume an upward trend. 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 also estimate correlations between any two elements of the estimated conditional covariance matrix. It appears that all such pair-wise correlations increase over periods of financial crisis, when compared to 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 estimated conditional variances of the UK and Japanese markets. As the elements of the conditional covariance matrix become more strongly correlated over the periods of bear markets, the benefits of international diversification decline when they are needed the most.

The rest of the paper is organized as follows: the econometric methodology is discussed in Section 1, while Section 2 describes the dataset and presents summary statistics for the data. Model estimates are presented in Section 3 and the last Section contains a conclusion.

1. Econometric specification

The conditional mean of the differenced log price series is specified as a vector error correction model:

$$\Delta P_t = c + \alpha(\beta' P_{t-1}) + \sum_{i=1}^{\kappa} \varphi_i \Delta P_{t-i} + u_i, \tag{1}$$

where $P_t = [P_{1t}, P_{2t}, P_{3t}, P_{4t}]'$ is a vector of $I(1)$ log prices, c is a (4×1) vector of constants, φ_i are (4×4) autoregressive coefficient matrices, while β' is a matrix of cointegrating parameters that consists of r cointegrating column vectors, and α 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 vector of innovations u_t conditional on the information set ψ_{t-1} is assumed to be conditionally normally distributed $u_t | \psi_{t-1} \sim N(0, H_t)$.

The time varying nature of conditional covariances between national stock markets (i.e. elements of H_t) has been well documented. For example, Koch and Koch (1991) reveal growing market interdependence in daily data using 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. 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. 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. In this paper, I use a similar time varying model to specify and decompose the conditional variance matrix H_t in the following manner:

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

Following Engle (2002) D_t is specified as a diagonal matrix of time varying standard deviations of dimension $(n\times n)$, while R_t is defined as a symmetric matrix of conditional correlation coefficients whose elements are pair-wise conditional correlations $\rho_{ij,t}$. The diagonal elements of H_t, the conditional variances, whose square roots are elements of 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:

$$h_{ii,t} = \varpi_i + \beta_i h_{ii,t-1} + \sum_{j=1}^{4} (\alpha_i + \delta_i I_{it-1}) u_{i,t-1}^2 \tag{3}$$

where $I_{it} = \begin{cases} 1 \,|\, u_{it} < 0 \\ 0 \,|\, u_{it} \geq 0 \end{cases}$.

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 R_t in the following way: standardized innovations e_t are first obtained by dividing market innovations u_{it} by their conditional standard errors $\varepsilon_t = \frac{u_{i,t}}{\sqrt{h_{ii,t}}}$ or $e_t = D_t^{-1} u_t$. The standardized innovations e_t are then assumed to be conditionally Normally distributed ($e_t \sim N(0, R_t)$). Further, the covariance matrix of the standardized residuals is identical to the correlation matrix due to the fact that its standard deviations equal one. This can be better seen by considering the relationship between the covariance and correlation below:

$$Corr(\varepsilon_1, \varepsilon_2) = \frac{Cov(\varepsilon_1, \varepsilon_2)}{\sqrt{Var(\varepsilon_1) Var(\varepsilon_2)}}. \tag{4}$$

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 (2006):

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}, \quad (5)$$

where

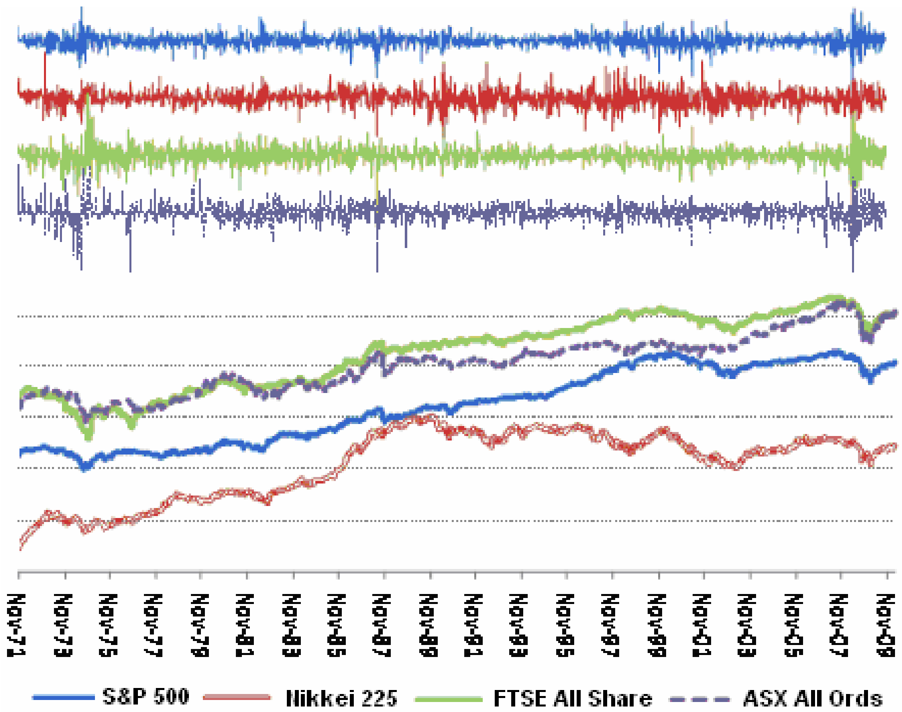
$$Q_t = \overline{Q}(1-a-b) - g\overline{N} + ae_{t-1}e'_{t-1} + bQ_{t-1} + g\eta'_{t-1}\eta_{t-1}, \quad (6)$$

where $\eta_t = I[e_t \prec 0] \cdot e_t$ isolates volatility shocks associated with negative return innovations. I also calculate $\overline{Q} = \frac{1}{T}\sum_{t=1}^{T} e_t e'_t$ and $\overline{N} = \frac{1}{T}\sum_{t=1}^{T} \eta_t \eta'_t$ to implement variance targeting.

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 meanand variance equations are correctly specified (Hamilton, 1994, p. 126). In this case, Bollerslev-Wooldridge (1992) standard errors are optimal.

2. 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 November 26, 1971 to April 09, 2010, and contains 2,003 weekly price observations. The data was obtained from DataStream® in common (USD) currency and the weekly frequency was chosen to circumvent the problems associated with non-synchronous data described in Burns, Engle and Mezrich (1998) and Martens and Poon (2001)[1].



Note: The top graph depicts index returns while the lower portion of the figure shows indices in log levels. (A different constant has been added to each return series in order to present them in one graph. This does not affect the patterns present in the series.)

Fig. 1. National stock market indices in returns and (log) levels

Even though the four series appear nonstatioary 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. 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).

As the graphs indicate, the return series are also consistent with the 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, the terrorist attacks of September 11, 2001, and the recent period of the Global Financial Crisis.

[1] 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.

2.1. Unit root tests. As previously mentioned and illustrated in Figure 1, the log-return series exhibit nonstationary behavior. 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 unit root. The Phillips-Perron test differs from the ADF test in that it accounts for autocorrelation non-parametrically.

Table 1. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests

	Levels		First differences	
	ADF	PP	ADF	PP
US	-1.76	-1.72	-47.13**	-47.09**
Japan	-1.50	-1.55	-29.79**	-45.65**
UK	-1.96	-2.23	-29.05**	-44.22**
Australia	-3.34	-0.81	-40.84**	-41.01**

Note: Levels refer to natural logarithms of variables so that the first differences are approximately percentage returns. 1% critical value for all tests is -3.926, 5% critical value is -3.412. ** denotes 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.

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

2.2. Cointegration tests. Next, I examine whether the national stock markets are cointegrated using Johansen (1988, 1991) tests by computing two related statistics: the Eigenvalue Trace statistic and the Maximum Eigenvalue statistic. Table 2 presents the results of the cointegration tests. 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 by noting that the four national markets are nonstationary but cointegrated with one cointegration vector or, alternatively, three common stochastic trends.

Table 2. Cointegration rank tests

Hypothesized no. of CE(s)	Trace statistic	5 percent critical value	1 percent critical value
None *	49.69*	47.21	54.46
At most 1	19.37	29.68	35.65
At most 2	9.18	15.41	20.04
At most 3	4.03	3.76	6.65
Hypothesized No. of CE(s)	Max-Eigenvalue Statistic	5 Percent Critical Value	1 Percent Critical Value
None *	30.32*	27.07	32.24
At most 1	10.19	20.97	25.52
At most 2	5.15	14.07	18.63
At most 3	4.03	3.76	6.65

Note: Cointegration tests are performed on log weekly returns over the period November 1971 – April 2010. 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).

3. Empirical findings

Estimates of the mean equation VECM specification are presented in Table 3 below.

Table 3. VECM estimates

Const.	US_t		JP_t		UK_t		AU_t	
Coef.	Coef	t-stat	Coef.	t-stat	Coef.	Coef	t-stat	Coef.
-0.70	-0.57	[-8.32]	-0.28	[-7.07]	1,00	-	-0.30	[-3.28]
VECM	ΔUS_t		ΔJP_t		ΔUK_t		ΔAU_t	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Speed of adjustment	0.006	0.14	0.011	0.04	0.013	0.01	0.013	0.02
ΔUS_{t-1}	-0.07	0.01	0.17	0.00	0.15	0.00	0.24	0.00
ΔUS_{t-2}	0.03	0.29	0.04	0.28	0.10	0.01	0.12	0.00
ΔJP_{t-1}	-0.02	0.40	-0.07	0.01	-0.02	0.50	-0.04	0.17
ΔJP_{t-2}	0.01	0.65	0.07	0.01	-0.01	0.82	0.03	0.18
ΔUK_{t-1}	0.06	0.00	0.03	0.32	-0.02	0.43	0.05	0.10

Table 3 (cont.). VECM estimates

VECM	ΔUS_t		ΔJP_t		ΔUK_t		ΔAU_t	
	Coef.	p-value	Coef.	p-value		Coef.	p-value	Coef.
ΔUK_{t-2}	0.02	0.37	-0.01	0.63	0.04	0.12	0.02	0.56
ΔAU_{t-1}	-0.03	0.11	0.00	0.88	-0.03	0.28	-0.01	0.38
ΔAU_{t-2}	-0.01	0.78	0.00	0.87	0.00	0.96	0.01	0.68
Const.	0.00	0.01	0.00	0.12	0.00	0.23	0.00	0.29
R-squared	0.02		0.03		0.02		0.05	

Diagnostic tests on residuals				
Jarque-Bera (J.B.)	3182.73	797.50	5014.15	25190.47
J.B. p-value	0.00	0.00	0.00	0.00
Q-stat (20)	7.30	22.20	31.45	20.61
Q-stat (20) p-value	0.20	0.23	0.06	0.42
Q-stat – squared (20)	483.40	238.40	625.79	226.92
Q-stat – squared (20) p-value	0.00	0.00	0.00	0.00
LM ARCH(5)	174.23	94.92	193.14	126.34
LM p-value	0.00	0.00	0.00	0.00

Note: The model is estimated on weekly returns over the period of November 1971-April 2010, t-ratios are given in parentheses. Grey areas point out rejection of null at a level smaller than 10%. Cointegrating vector is normalized on the UK market coefficient.

The speed of adjustment coefficients for the UK, Japan and Australia are statistically significant at the 1 per cent level, while the US coefficient is insignificant. The coefficients are of largest magnitude in the UK and Australian equations, although typically low, with adjustments to deviations from the long-run equilibrium of about 1.3 per cent per week. 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 5 per cent. The lagged US returns are found to be statistically significant for the other three markets.

The lower portion of Table 3 presents a number of model diagnostic tests. Although the Jarque-Bera statistics indicate non-Normality in the estimated residuals, the Ljung-Box Q-statistics (for up to 20 lags) suggest that the VECM filters out autocorrelation quite well. The autocorrelation, however, remains present in squared residuals as indicated by high Q-statistics computed on squared residuals with p-values equal to zero to two decimal places. As the presence of autocorrelation in the squared residuals is typically associated with time-varying conditional volatility I also report estimated LM ARCH tests (Engle, 1982). The tests confirm ARCH type behavior in the residuals and this is modeled next in the ADCC framework.

3.1. Conditional volatility, correlations and volatility spillovers. As illustrated in Table 4 below, all conditional variance equations exhibit asymmetric behavior associated with negative news shocks. Further, bi-directional volatility spillovers are recorded between the US and the UK, and between Australia and Japan. 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 contains both symmetric and asymmetric terms. 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 spills over volatility to Japan with volatility transmissions of the same magnitude for positive and negative news.

Table 4. Conditional second moment matrix parameter estimates

Volatility equation for:	US		Japan		UK		Australia	
	coef.	p-val	coef.	p-val	coef.	p-val	coef.	p-val
Volatilty spillover from:								
US	-	-	0.05	0.04	-0.01	0.46	-0.02	0.31
US (Asym.)	-	-	-0.01	0.82	0.09	0.08	0.10	0.20
Japan	0.00	0.38	-	-	0.00	0.75	0.02	0.16
Japan (Asym.)	-0.01	0.12	-	-	-0.01	0.54	-0.04	0.08
UK	-0.01	0.07	-0.01	0.17	-		0.01	0.70
UK (Asym.)	0.02	0.04	0.00	0.70	-	-	0.06	0.16
Australia	0.01	0.45	-0.03	0.00	0.00	0.71	-	-
Australia (Asym.)	-0.01	0.57	0.03	0.00	-0.01	0.66	-	-

Table 4 (cont.). Conditional second moment matrix parameter estimates

Volatility equation for:	US		Japan		UK		Australia	
	coef.	p-val	coef.	p-val		coef.	p-val	coef.
GJR(1,1,1) Parameters								
α (Arch)	0.03	0.03	0.05	0.00	0.06	0.01	0.00	0.94
δ (Asym. Arch)	0.12	0.00	0.12	0.00	0.07	0.02	0.06	0.04
β (Garch)	0.86	0.00	0.81	0.00	0.84	0.00	0.87	0.00
Correlation parameters:								
a			0.010	0.04				
g			0.004	0.07				
b (Asym.)			0.985	0.00				

Note: The model is estimated on weekly returns over the period of November 1971-April 2010. Grey areas point out p-values smaller than 10%. P-values are calculated using Bollerslev-Wooldridge (1992) robust standard errors.

The conditional correlation equation parameters are given in the lower portion of the above. The coefficients sum to just below one indicating a high level of persistence in conditional correlations. An asymmetric correlation term is also statistically significant at the 10 percent level, indicating that conditional correlations increase during periods of negative news shocks. This is confirmed by a visual inspection of the estimated conditional correlation series, which are presented in Figures 2 and 3 below.

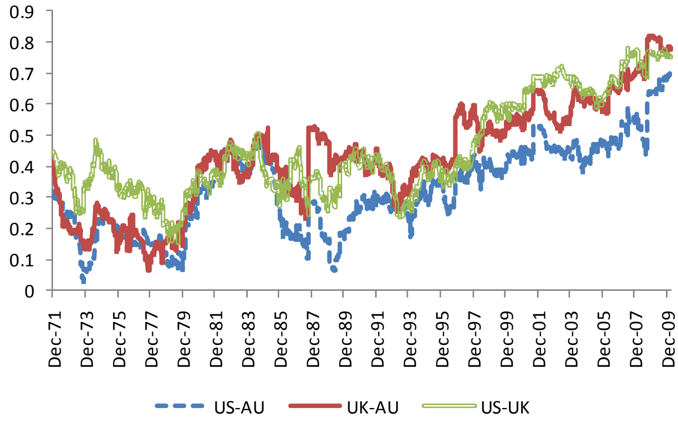


Fig. 2. Estimated weekly conditional correlations (US-AU, UK-AU, US-UK)

We can make three main observations about the above graph. First, in accord with the asymmetric component of the conditional correlation equation, which is statistically significant at the 7 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 1973-1974, the stock market crash of 1987 and more recently, although not of the same magnitude, the 11/9/2001 terror attacks. Lastly, we observe a clear upward trend in the correlations that starts at the end of 1993.

Estimates of the conditional correlations for the US-Japan, UK-Japan, and Japan-Australia market pairs are presented in Figure 3. The three correlations involving Japan follow similar time series patterns along a relatively stationary path until the end of 2001, after which they assume an upward trend. The three correlations peaked in 2008 and have since decreased.

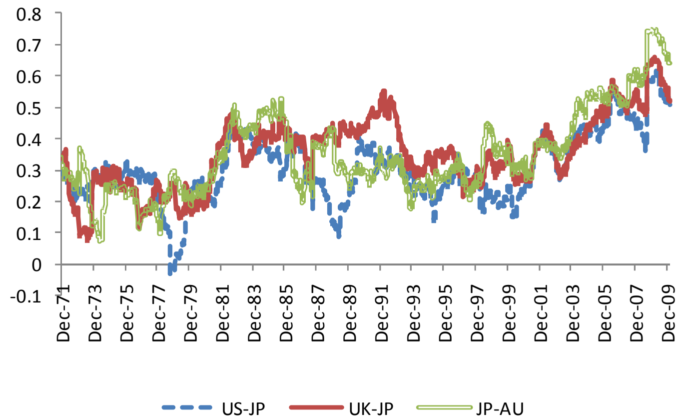


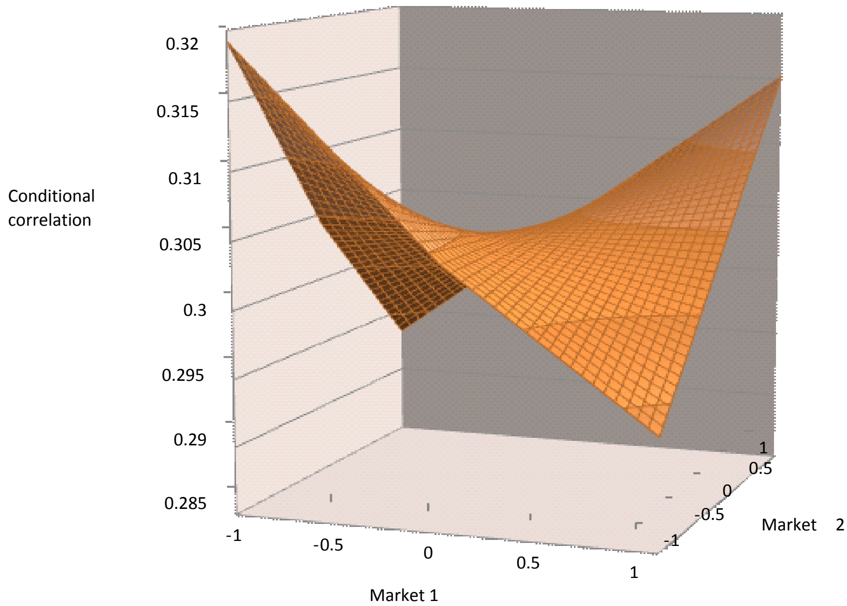
Fig. 3. Estimated weekly conditional correlations (US-JP, UK-JP, JP-AU)

3.2. Effects of asymmetric responses to bad news. All conditional volatilities and correlations exhibit asymmetric responses to bad news as illustrated in Table 4. Further, all four markets also receive asymmetric volatility spillovers from other markets. In this section, I illustrate interactions of the estimated correlations and volatilities 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:

$$\sigma_{pt}^2 = \sum_{i=1}^{N} w_i^2 \sigma_{it}^2 + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} w_i w_j \rho_{ijt} \left[\sigma_{it}^2 \sigma_{jt}^2 \right]^{1/2} \quad (7)$$

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 4), 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'? The asymmetric effect associated with bad news is illustrated graphically using a news impact surface in Figure 4 below.



Note: According to the scaler version of the ADCC model, Eq. (6), the conditional pairwise 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.

Fig. 4. Conditional correlation news impact surface

The above picture clearly depicts the effect of the asymmetric response to negative news in conditional correlations. The conditional correlation impact surface reaches its maximum value when both markets receive negative news, a point corresponding to the left-hand corner in the graph. The correlations are clearly smaller when both markets are shocked by positive news at the same time, and reach their minimum values when one market receives positive news while the other market receives negative news.

In order to further quantify the effects that financial crises have on the conditional covariance matrix Table 5 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. Correlations between estimated conditional variances and correlations

	h_t^{us}	h_t^{jp}	ρ_t^{us-jp}		h_t^{jp}	h_t^{uk}	ρ_t^{jp-uk}
h_t^{us}	1.00	0.32	-0.05	h_t^{jp}	1.00	0.05	0.13
h_t^{jp}	0.92	1.00	0.05	h_t^{uk}	0.89	1.00	-0.17
ρ_t^{us-jp}	0.23	0.16	1.00	ρ_t^{jp-uk}	0.17	0.25	1.00
	h_t^{us}	h_t^{uk}	ρ_t^{us-uk}		h_t^{jp}	h_t^{au}	ρ_t^{jp-au}
h_t^{us}	1.00	0.65	0.14	h_t^{jp}	1.00	0.11	0.04
h_t^{uk}	0.97	1.00	-0.07	h_t^{au}	0.87	1.00	-0.18
ρ_t^{us-uk}	0.15	-0.01	1.00	ρ_t^{jp-au}	0.12	0.16	1.00
	h_t^{us}	h_t^{au}	ρ_t^{us-au}		h_t^{uk}	h_t^{au}	ρ_t^{uk-au}
h_t^{us}	1.00	0.77	0.03	h_t^{uk}	1.00	0.82	-0.25
h_t^{au}	0.97	1.00	-0.15	h_t^{au}	0.98	1.00	-0.16
ρ_t^{us-au}	0.12	0.05	1.00	ρ_t^{uk-au}	0.13	0.14	1.00

Note: 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 shocks, 17/10/1987 – 4/12/1987 stock market crash, 19/12/1994 – 31/12/1994 Mexican Peso Crisis, 7/9/2001 – 12/10/2001 September 11, 2001, terrorist attacks, and the Global Financial Crisis 01/08/2007 – end of sample.

All market pairs share a similar pattern with 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 number of correlations between estimated volatility and conditional correlation series turns from weakly negative to moderately positive. These dramatic changes brought on by global bad news shocks highlight the effect of asymmetric responses that have been frequently cited in the literature (e.g., Cappiello, Engle and Sheppard, 2006; and Ang and Bekaert, 2002).

Conclusion

Time series dependencies are measured among the national stock markets of the US, the UK, Japan and Australia using long-run cointegration, conditional correlations and volatility spillovers over the period November 1971 to April 2010.

The four markets are found to be cointegrated with one vector but adjust to deviations from the long-run equilibrium relatively slowly. The explanatory power of the VECM for weekly returns is small, from 2 per cent for the US and UK markets to 5 per cent for the Australian market. An implication of these findings is that cointegration is unlikely to reduce diversification benefits over short-to-medium investment horizons, although it may diminish then over longer periods.

Asymmetric responses to negative news are found in volatilities, correlations as well as volatility spillovers. Bidirectional volatility spillovers are found between the US and UK, and between Japan and Australia. Weekly conditional correlations exhibit time varying behavior and some common features. The correlations between the US, the UK and Australian stock markets exhibit an upward trend over the 1993-2010 period, while the correlations that involve Japan assume a similar upward trend at the end of 2001.

In order to measure the effects of the dependencies uncovered here I plot a correlation impact surface and calculate correlations between any two estimated variance/correlations series. These correlations increase for most of the estimated variance/correlation pairs during periods of financial crises. The largest increase of *eighteen* times is recorded between the realized variances of the UK and Japan.

The above reported findings of asymmetries coupled with the finding of cointegration among the national stock markets suggest that common negative shocks can be regarded as regularity rather than an aberration. This emphasizes the importance of taking the asymmetries into account when constructing risk management tools and policies, and failing to do so may result in a significant underestimation of risk.

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