

# **The Correlation of Stock and Bond Returns: A Comparison between U.S. and Australia**

**Victor Fang<sup>a</sup>  
Yee Choon Lim<sup>b</sup>**

**a,b Department of Accounting and Finance  
Monash University,  
P O Box 197, Caulfield East, 3145, Victoria, Australia.  
a, [victor.fang@buseco.monash.edu.au](mailto:victor.fang@buseco.monash.edu.au)  
b, presenter of paper at Conference.**

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## **Abstract**

Sufficient theory and evidence about comovement between stocks and bonds are documented in the past to suggest that volatility transmission exists, although a consensus to causation and prediction has yet to be reached. The portfolio theory accords both assets with complimentary characteristics, thus being a premise to our conjectures about cross-market linkages. As such, we investigate the cross-market informational dependence between these assets under disparate interest rate conditions of the U.S and Australia. With conditional variance as a proxy for volatility, we use the BEKK- a matricular decomposition of the bivariate GARCH (1,1) model to examine the cross-market contemporaneous effect of information arrival. Applying the model to the stock and bond indices of both countries, we find evidence of volatility spillover, thereby supporting the notion of informational dependence between each market.

# **The Correlation of Stock and Bond Returns: A Comparison between U.S. and Australia**

## **Introduction**

The U.S. financial markets are widely regarded as being most vital to global capital intermediation. There exist transmission mechanisms bonding other international markets to the U.S. that fashion a central role of information dissemination for the latter. Therefore, an interaction between the U.S and its peripherals are expectable in the event of market shocks. In extremity, markets also witness contagion effects and this motivates us to explore the possible linkages between the domestic market and that of the U.S. with practical implications for two major participants: portfolio holders and policy makers. Under varying economic circumstances, the flow of capital is observable through the volatility of asset returns. As shown in past research, any relation is likely to be temporal since the impounding of information is merely contemporaneous, not instantaneous. As such, portfolio holders are concerned with the relation between assets as they seek diversification. If the variability of assets they hold is related, then, the benefits of diversification may be overstated. Likewise, policy makers must be aware of fiscal and monetary implications that arise from the influences of other major markets.

Our interest involves two main conduits for international capital allocations: stocks and bonds. These assets are accessible and possess rudimentary features, thus being attractive to the common investor. Given that the underlying cash flows of both asset classes are complimentary, there is consensus on the benefits of an optimal allocation of each in a portfolio. As propounded by Merton (1974), corporate bondholders can be seen as sellers of put options to shareholders of the firm. If the volatility of the mean cash flow of the firm increases, the value of the put options should follow suit. For this reason, it is expectable that informed investors will actively rebalance their portfolios in reception<sup>1</sup> of new publicly available information. If new information suggests that the mean future cash flow of the portfolio is likely to be more volatile or uncertain, the investor will

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<sup>1</sup> Ross (1989) is the first to demonstrate that variance of price movements has a direct relationship with the rate of release of information under no-arbitrage conditions.

accordingly adjust her asset composition to lower the variability of portfolio returns. This is viable by increasing the holding of fixed income securities: investment grade bonds in particular, since they are the highest yielding liquid assets. Conversely, if an expansionary period is expectable, then the investor will reallocate her assets favoring stocks, in order to capitalize on its higher expected mean. The phenomenon is widely referred as “flight to quality”, it follows between both asset classes and their countries of origin, for well-informed investors are perfectly mobile. This provides a premise to informational linkages across different assets and their country of origin. Whilst portfolio rebalancing occurs contemporaneously after information is available to the markets, the process should be recursive over time and therefore, information linkages between them are omnipresent and a causal relation should exist. Our conjectures are further justified by the evidence found by Campbell et al. (2001). They show the upward trend of idiosyncratic volatility in the U.S. stock markets did not result in a similar increase in systematic volatility, suggesting that diversification has been taking place by selling bonds: as witnessed by the depression of bond prices. Campbell and Taksler (2003) present new evidence on this phenomenon by using equity volatility to explain the increase in bond returns.

Intuitively, investors are more active in diversifying their portfolios either in anticipation or in precedence<sup>2</sup> of shocks to the markets. Following events that induce uncertainty, trade volume is likely to fall: but diversification activity<sup>3</sup> still takes place. In fact, diversification activity may rise after negative shocks since investors become more wary of the uncertain conditions. Hence, trade volume, prices and mean returns alone does not completely reflect the causality between demand for complimentary assets such as stocks and bonds. Assuming that portfolio holders dominate market activity after an unanticipated negative event, then, it is reasonable to contend that the conditional variances of returns (instead of their absolute means) of these complimentary assets is likely to reveal the behavior of investors. Simply, if investors are collectively selling an asset for another, then, causality is observable in the conditional variance of returns rather than its mean. As mentioned, the process is consequentially, recursive; and thus, causality

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<sup>2</sup> The strengthening of cross-market linkages after an international market shock is evident in Fleming et al. (1998).

<sup>3</sup> That is, there may be fewer entrants into the market, but existing portfolio holders will be looking for means of diversification

of the behavior of investors is inferable from the volatility of returns of the assets involved. Nonetheless, time is required for a complete response since markets are not “frictionless” and the behavior of participants, not homogenous. With these grounds, Engle, Ito and Lin (1990) justify the use of conditional variances since the willingness (unwillingness) of investors to sell (buy) an asset amidst uncertainty reveals the measure of information they rely on.

The use of conditional variances as proxies of information transmission is particularly appealing in the study of informational linkages, as it has been widely documented that volatility is predictable. The proverbial (finance) meteor shower and heat wave epitomizes the volume of research in this concern. Yet, to our knowledge, investigation in the context of asset portfolios (as discussed above) is sparse. Hence, if investors seek to maximize the financial returns of their portfolio, causality in ARCH behavior (variance) of both the stock and bond markets is expectable. Above that, the relation should be easily observable under markets of disparate interest rate environments such as that of the U.S. and Australia. Finally, with the given premises, we posit that informational linkages arising from portfolio investment of both assets conjugates information linkages between both markets (countries); and the relation is explainable vis-à-vis volatility spillovers and clustering.

### **Literature Review**

In general, research suggests a correlation between stock and bond returns on an aggregate level, while limited evidence present minor disparities. Consistent with the conventional expectations model, Shiller and Beltratti (1992) find substantial evidence on a strong negative correlation between variability in real stock prices and long-term interest rates of the U.S. and U.K. financial markets. Campbell (1993) adopted an endogenous approach and decomposed stock and 10-year bond returns. He found that variability of stock and bond returns are conditional on future excess stock returns and inflation. Furthermore, real interest rates do not seem to have an impact, thus explaining the low correlation between excess stock and bond returns. On individual firm basis, Kwan (1996) observe that stocks returns lead current bond yields (negatively), thus justifying the postulates of higher efficiency in the stock markets. Inconsistent with

studies on the aggregate level, his findings also show that the relation is robust only in conditional mean of the underlying assets of the firm, rather than its variance.

Recent evidence of linkages between markets has been demonstrated through the causality in variance approach. Caporale et al. (2002) applies the test to East Asian markets<sup>4</sup> and find a causal relationship between stock prices and exchange rates volatility. Bhar and Hamori (2003) use a slightly different methodology and find that the stock markets for all countries in the G7<sup>5</sup> are related to the U.S. Most interestingly, Japan causes other countries in mean and these countries reciprocate in variance, implying that, volatility spillovers are bi-directional, albeit unconvincing<sup>6</sup>. Stronger evidence emanate from Alaganar and Bhar (2003) as they observe causality in both mean and variance of the financial sector returns and short-term interest rates of the G7.

Gathering the existing evidence, we find a plausible relation between international stock and bond diversification such that volatility transmission forms informational linkages between these markets. We expect causality to be observable between countries as witnessed by local markets although it may be inconsistent since other confounding factors inherent of international markets may govern the relation. Hence, this provides us several reasons to attempt a different study. First, current theorists and empiricists have already provided substantial explanations to local markets and have yet explored the possible relations in international markets. Second, most of these studies involve homoscedastic modeling which disregards the time-varying nature of financial returns. This is particularly important since these studies seek to explain long-term relations tend to ignore the contemporaneous effects of information. Moreover, disparity commonly exist in both cases.

The next section outlines the data set, followed by a description of causality in variance test introduced by Cheung and Ng (1996) and Caporale et al. (2002). We present a thorough analysis of the empirical evidence thereafter, and the concluding remarks are in the final section.

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<sup>4</sup> They are Indonesia, Korea Thailand and Japan.

<sup>5</sup> They are essentially the G8 OECD countries, excluding Australia.

<sup>6</sup> The use of monthly data and Markov method of extrapolating variance may not truly represent market movement.

## **The Data**

To obtain an unbiased representation of confounding informational effects, we employ daily data of the stock and bond indices for both the U.S. and Australia over the period<sup>7</sup> of 6/30/1998 to 11/14/2003. This sample period encapsulates volatility inducing events such as the devaluation of the ruble, the technology bubble, September 11<sup>th</sup> and the Middle-Eastern political uncertainty. As most time-series studies on volatility involve large samples and singular structural breaks, they tend to neglect confounding effects of other events within the sample period. In our opinion, the problem inherent of a single structural break and the large sample require (of volatility studies) tend to lead to inferential complications, such that sources of volatility is difficult to identify and their effects are difficult to capture. Hence, we reason our choice of sample period based on the objective of understanding the causality of informational transmission between both assets over a given period, rather than explaining the effects of a single event.

The sample period also captures the disparity in interest rates, which may lead to the increased awareness of the benchmark rates in Australia. Shown in Exhibit 1, the cash rate of both countries are in tandem prior to May 2001, and starts to diverge thereafter. By September 2003, the interest rate differential was higher than 4 per cent. However, due to the availability of data control measures, we are unable to extend the sample period.

[Exhibit 1 about here]

The stock and bond index data for the U.S is available from Dow Jones: Dow Jones Industrial (DJI) and the Dow Jones Corporate Index (DJCI). The DJI is a value weighted market aggregate index, while DJCI is a composition of investment grade bonds issued by 96 corporations in the U.S. For Australia, we use the Australia Stock Exchange All Ordinaries Price Index (ASXAO) and Australian Bond Index (ABI) available in Datastream. By construction and composition, all four indexes used in our analysis are

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<sup>7</sup> The Australian Bond Index was initiated in 30<sup>th</sup> of June 1998, and thus it forbids us from obtaining a desirable (larger) sample size. Nonetheless, this should not prevent us from drawing reasonable inferences since any biasness inherent from distributional complications can be compensated by strict rejection criterion.

able to capture volatility arising from systematic influences as they consist of firms from different industries, and thus are able to reflect general informational effects. Nonetheless, we observe a caveat in the use of bond indexes owing to the nature of the security. Returns are dependent on various characteristics such as duration and convexity. Therefore, it is ideal that corporate bond of differing maturities are well distributed in the index. The construction of the DJCI and ABI satisfies these conditions.

Cursorily, volatility for stocks is much higher than bonds for both countries (See exhibit 2 and 3) while U.S stocks series display more clustering than the Australian counterpart does. Exhibit 4 presents a summary of the descriptive statistics of all four series. The sample size of 1402 is relatively small for modeling volatility thus explaining the low Ljung-Box statistics for the standardized squared residuals. The sample moments for all four series show heavy skewness while the distributions are leptokurtic.

[Exhibit 2, 3 and 4 about here]

### **Methodology**

Empirical evidence presented by Shiller and Beltratti (1992), Kwan (1996) and Campbell (1993) demonstrates a negative correlation between stocks and bonds, albeit to varying degrees. Although the methods employed are robust to their study, however, they have shown neglect to the informational role of variance in financial time series. This motivates us to investigate the causality between both assets via temporal volatility. Moreover, it is common knowledge that variance of returns indicates the flow of information between investors. Therefore, if causality is observable in variance, these assets (and their markets) should be information-linked.

Cheung and Ng (1996), Caporale et al. (2001) and Bhar (2003) have developed several variations of measuring causality-in-variance. Of which, the earliest method was devised by Cheung and Ng (1996); they use the residual cross-correlation function (CCF) on conditional mean and conditional variance estimates obtained from univariate time-series models. Interestingly, orthogonal relations in both variables are possible *per se*; a relation may exist in either moment. This furthers our concern for any possible unobserved causality in the second moment.

Instead of using the GARCH (1,1), Bhar (2003) employed the Markov Switching process to model conditional variances (on stock returns) based on an unobserved state. The model estimation relies on a probability weighted maximum likelihood function, and allows a smooth distribution of conditional variances that are suitable for a causality-invariance test. Although the model is theoretically appealing as it addresses the martingale behavior of financial markets, however, its estimates discard informational effects represented by daily volatility, which is of primary concern in the study of linkages.

Caporale et al. (2001) augment Cheung and Ng (1996) with the BEKK model<sup>8</sup>, which parameterizes conditional variances, covariance and their cross-correlation. Suitably, the model is applicable to two or more variables in both moments while not requiring excessive estimation of parameters; and alleviates complications arising from re-parameterization (inherent of the VAR). In addition, the quadratic specification allows us to treat problematic negative covariance matrices faced by other specifications (such as the VECH) without difficulty.

Given the properties of the techniques discussed, we employ the multi-variate GARCH (1,1) – BEKK representation (Engle and Kroner (1995)) to model the relationship. First, it requires an estimate of the conditional variances from the GARCH (1,1) model<sup>9</sup>:

$$Y_t = \mu + \beta X_{t-1} + \varepsilon_t \quad (1)$$

Where  $Y_t$  denotes the returns on the stock index  $SI_t$  and bond index  $BI_t$ . The disturbance term  $\varepsilon_t$  is bivariate and normally distributed  $u_t | \Phi_{t-1} \sim (0, H_t)$  with its corresponding vectors  $e_{1,t}, e_{2,t}$ .

In a univariate GARCH (1,1) process, the conditional variance  $\sigma_t^2 | \Phi_{t-1}$  is obtained from the variance equation (2). We adopt the BEKK representation, which is essentially a spectral decomposition of the conditional variance-covariance matrix. A multivariate GARCH(1,1) model (3) is resultant of the operation.

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<sup>8</sup> The BEKK (Baba-Engle-Kraft-Kroner) model is adopted by Baba et al. (1987).

<sup>9</sup> Bivariate Garch (1,1) representation in Engle and Kroner (1995)

$$\sigma_t^2 = \mu + \alpha_1 \varepsilon_{t-1} + \beta \sigma_{t-1}^2 \quad (2)$$

$$H_t = \Omega' \Omega + \alpha' \varepsilon_{t-1} \varepsilon_{t-1}' \alpha + \beta' H_{t-1} \beta \quad (3)$$

The spectral decomposition is as follows:

$$H_t = C_0' C_0 + \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} e_{1,t-1}^2 & e_{1,t-1} e_{2,t-1}' \\ e_{1,t-1} e_{2,t-1}' & e_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \quad (4)$$

$$+ \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

The BEKK (3) decomposes the GARCH (1,1) process into its multivariate constituents and models the time-varying process of  $H_t$  conditional on the lag values of the residuals of the mean and variance equation. The model facilitates the interaction between the conditional variances and covariances thus allowing us to observe the correlation of information arrival upon two different markets. The matrix is restricted to upper and lower triangles to observe the bidirectional causality. Following the above, we test for the hypothesis of causality in conditional variances between the bond and stock markets within the country and between the individual assets of both countries. The co-efficient estimates are obtained from the log likelihood function:

$$L = \sum \log f(Y_t | \Phi_{t-1}; \theta) \quad (5)$$

The conditional density function for the log likelihood estimates is:

$$f(Y_t | \Phi_{t-1}; \theta) = (2\pi)^{-1} |H_t|^{-1/2} \exp\left(-\frac{u_t'(H_t^{-1})u_t}{2}\right) \quad (6)$$

where  $\theta$  is the vector of unknown parameters and standard errors are obtained from the quasi-maximum likelihood method by Bollerslev and Wooldridge (1992).

## **Empirical Results**

Exhibit 5 presents the co-influences of mean and conditional variances of both assets in the U.S. and Australia. We are aware of the distributional complications arising from a relatively small sample size, which is a circumscription of the unavailability of an appropriate bond index. As such, to account for distributional complications, we take the population of the ABI and restrict our inferences to 1 per cent significance in order to compensate for any biasness that may arise.

[Exhibit 5 about here]

In contrast to *a priori* knowledge, the coefficient estimates of bidirectional causation in the conditional variances of both assets in the U.S indicating that volatility spillover does not occur between stocks and bonds on the aggregate, albeit some evidence is present if we lower the rejection criterion to 5 per cent. The interaction terms are significant under the 10 per cent rejection region, suggesting that bidirectional volatility transmission is palpable although we are inclined not to make any inferences. Given that the Australian economy has been operating in a relatively high interest rate environment, international investors are likely to be more sensitive to the available benchmark rates (Australian treasury securities and investment grade bonds), thus explaining the possibility of bidirectional causation.

The cross-market analysis presents a more comprehensive account of information transmission. We find strong evidence of interaction between the stock and bond markets of both the U.S. and Australia. The significant positive coefficients of unidirectional volatility transmission from the U.S. to Australia shown in exhibit 6 and 7 are consistent with our proposition. Thus, this leads to the falsity that Australia is a sanctuary for risk adverse investors, given that, volatility precipitates in the U.S.

[Exhibit 6 and 7 about here]

The most interesting aspect of our study lies in the evidence of “flight to quality” from the U.S stock market to the Australian bond market. The statistically significant negative coefficient  $\beta_{12}$  (exhibit 7) of volatility transmission from the U.S stock provides for our conjecture of international diversification of substitute assets. It is apparent that investors are outweighing U.S stocks with Australian bonds in anticipation of uncertainty. The negative relation suggests that higher uncertainty in the U.S stock market within the sample period transmits information that leads to lower uncertainty in the Australian Bond market. The fact that Australian investors face a relatively higher benchmark rate compared to U.S. over the sample period supports our findings since it is reasonable to expect international investors to be actively seeking higher foreign benchmark rates that the domestic markets are not able to provide for. Laterally speaking, Australian bond portfolio holders may also short sell U.S. stocks during times of uncertainty.

### **Concluding Remarks**

Our study elucidates the herding behavior of investors given both complimentary assets. The high (rising) interest rate environment and the perceived resilience of the Australian economy provide us with a unique opportunity to investigate the informational dependence between stock and bond investors in both countries. As bond returns represent benchmark rates, it is reasonable to contend that a noticeable number of informed investors will fashion their portfolios to capitalize on the bond market of Australia. Therefore, we conduct an analysis in the given circumstance.

We apply the GARCH (1,1) – BEKK representation by Engle and Kroner (1995) and extend the analysis of spillover effects from the stock market to the bond market involving two countries: U.S. and Australia. By using the conditional variance as a proxy for volatility, we find substantial evidence in bidirectional cross-market influence in the Australian stock and bond markets. The use of conditional variance as a measure of volatility causation to compliment the mean are in several studies such as Cheung and Ng (1996) and Caporale et al. (2002). They argue that the conditional variance provides a

different dynamic to volatility and conclude that its distributional robustness allow reliable inferences.

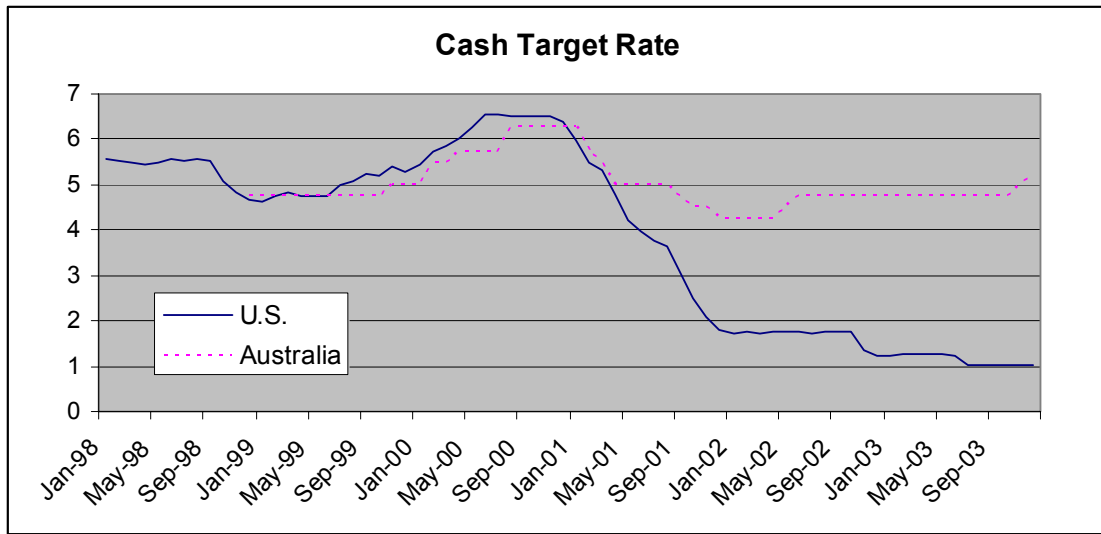
Further tests on markets between both countries yield interesting results. Statistics reveal the spillovers between the stock markets of the U.S and Australia, and the same effects are present in the bond markets of both countries. Most interestingly, the bond market of Australia exhibits informational dependence on the stock market of the U.S, even though we find no corresponding evidence in the bond market of the latter. The occurrences of volatility transmission are both persistent in the mean and conditional variance, thus providing confidence for the analysis although the sample period is relatively small. Moreover, we have taken extreme precautions in preventing a type I error by drawing inferences within high rejection regions.

While evidence of feedback effects to the U.S. (particularly in currencies) is widely documented, we do not extend our analysis, owing to the unsuitability of data in the G8 countries. Another point to consider: the lagged dependence of conditional variances is not observable with the BEKK representation, consequently forgoing further evidence of causality. The aforementioned will be the object of our future research.

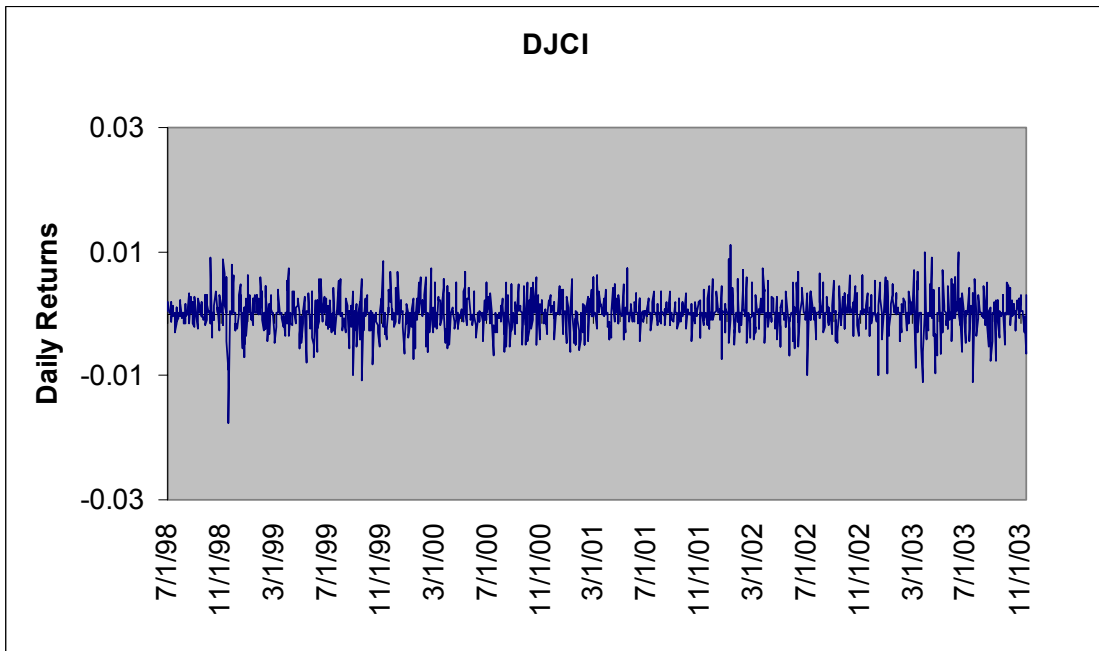
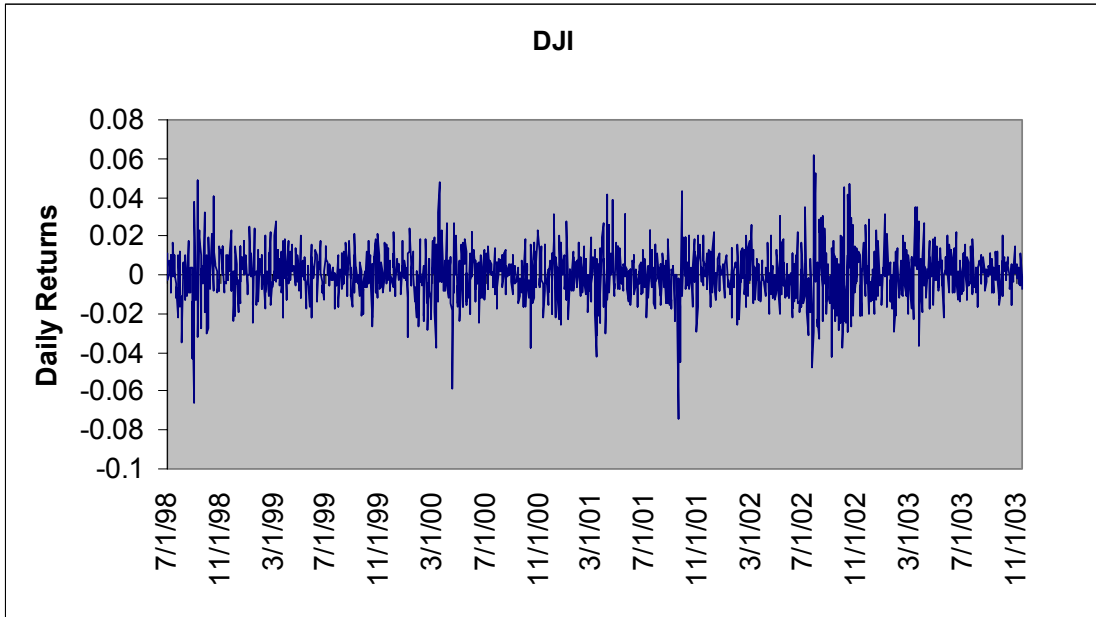
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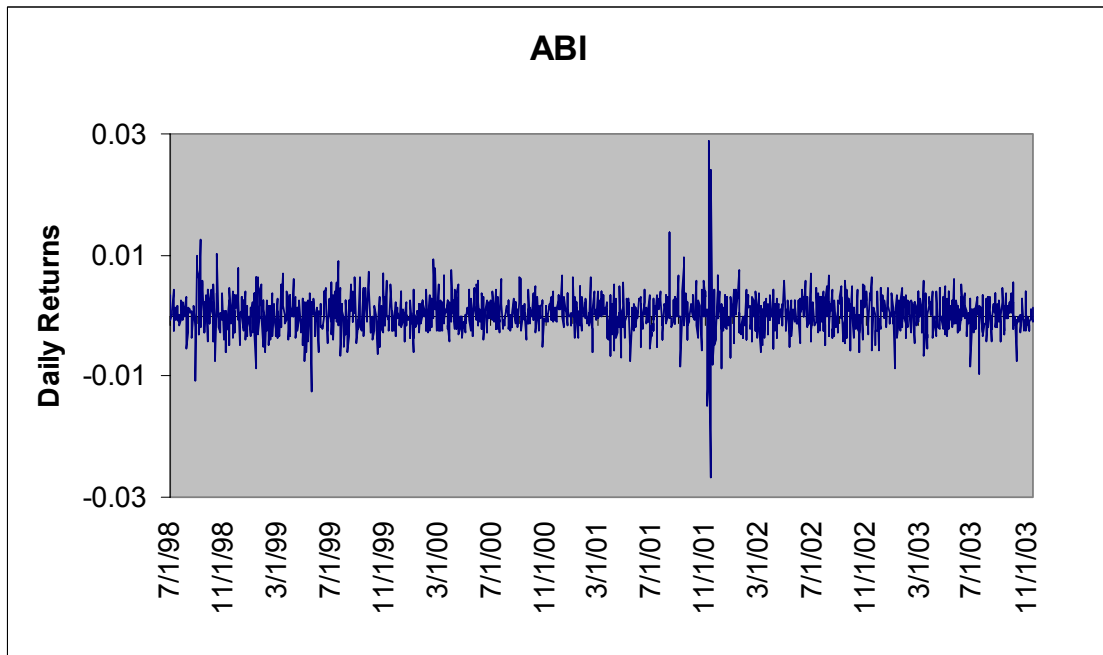
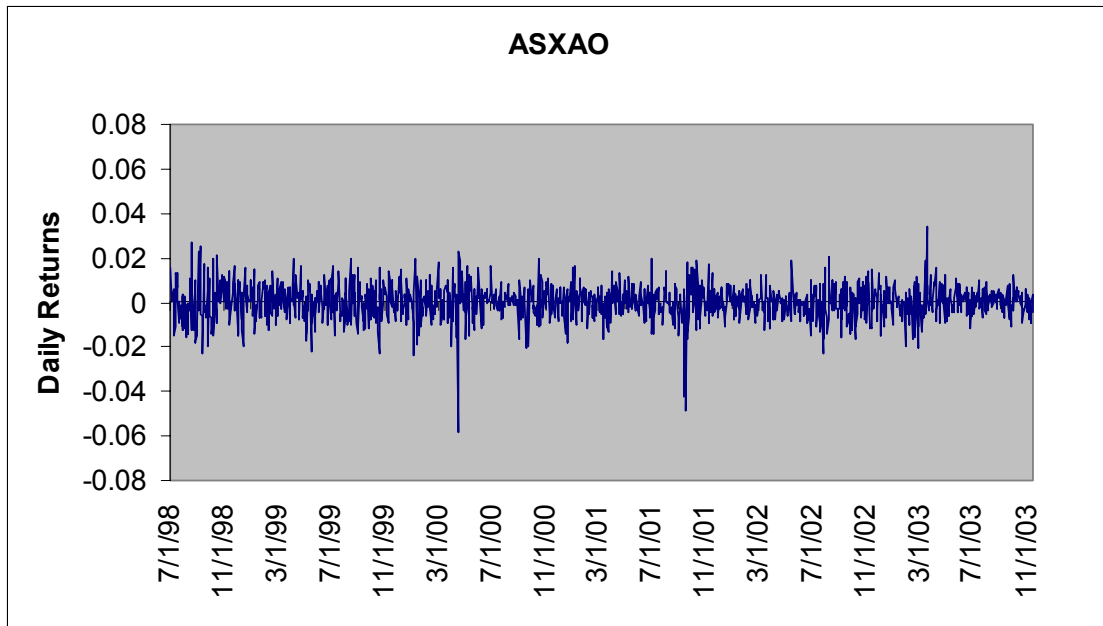
**Exhibit 1**



**Exhibit 2**



**Exhibit 3**



## Exhibit 4

### Descriptive Statistics

	US		Australia	
	DJI	DJCI	ASXAO	ABI
<b>Mean</b>	0.00006	0.00015	0.00013	0.00021
<b>Median</b>	0.00000	0.00019	0.00003	0.00001
<b>Maximum</b>	0.06155	0.01110	0.03387	0.02892
<b>Minimum</b>	-0.07396	-0.01767	-0.05853	-0.02690
<b>Std. Dev.</b>	0.01294	0.00273	0.00776	0.00316
<b>Skewness</b>	-0.09364	-0.36638	-0.51711	0.30152
<b>Kurtosis</b>	5.63168	6.11326	7.17430	14.41433
<b>Jarque-Bera</b>	406.916**	597.9893**	1081.149**	7637.622**
<b>LB(SSR)</b>	56.4*	160.7**	67.7792*	304.4624**

Sample period from 7/01/1998 to 11/14/2003

\* indicates significant at 10%

\*\* indicates significance at 5%

## Exhibit 5

### Summary of Estimates for Bidirectional Volatility Spillover for Individual Countries

The table presents the coefficient estimates from the bivariate GARCH (1,1) – BEKK representation. The co-efficient estimates are obtained from the maximum likelihood function of the bivariate model. Coefficient  $\beta_{12}$  denotes volatility transmission from the stock market to the bond market, while  $\beta_{21}$ , vice versa.

U.S. DJI and DJCI					Australia ASXAO and ABI			
	Coefficient	Std. Error	z-Statistic	P-Val	Coefficient	Std. Error	z-Statistic	P-Val
$\mu_{11}$	0.00031	0.000321	0.967221	0.3334	0.0003	0.0002	1.6974	0.0896
$\mu_{22}$	0.000203	7.03E-05	2.883744	0.0039	0.0002	0.0001	2.7433	0.0061*
$\Omega_{11}$	0.002058	0.000303	6.782009	0.00*	0.0014	0.0002	7.1155	0.00*
$\Omega_{12}$	0.0007	0.0010	0.7573	0.4489	-0.0003	0.0001	-3.2134	0.0013*
$\Omega_{21}$	0.00043	0.00028	1.53712	0.12430	-0.000426	0.000212	-2.004658	0.045
$\Omega_{22}$	0.0023	0.0003	7.5841	0.00*	0.0008	0.0001	8.0953	0.00*
$\alpha_{11}$	0.2552	0.0193	13.2005	0.00*	0.2664	0.0168	15.9002	0.00*
$\alpha_{12}$	0.0052	0.0093	0.5642	0.5726	-0.0001	0.0091	-0.0156	0.9876
$\alpha_{21}$	0.16298	0.06926	2.35298	0.01860	-0.071154	0.045581	-1.56105	0.1185
$\alpha_{22}$	0.4409	0.0287	15.3350	0.00*	0.2525	0.0125	20.2635	0.00*
$\beta_{11}$	0.9540	0.0074	129.7735	0.00*	0.9485	0.0084	112.8578	0.00*
$\beta_{12}$	-0.0124	0.0143	-0.8663	0.3863	0.0066	0.0037	1.7966	0.0724
$\beta_{21}$	-0.05340	0.02586	-2.06527	0.03890	0.05008	0.029224	1.713663	0.0866
$\beta_{22}$	0.1455	0.1670	0.8713	0.3836	0.9272	0.0128	72.5977	0.00*
	$\beta_{12}$	$\beta_{21}$			$\beta_{12}$	$\beta_{21}$		
Log LL	10494.78	10697.88			11090.92	11091.18		
Ave. Log LL	7.48558	7.630442			7.910781	7.910973		
AIC	-14.9555	-15.24519			-15.80587	-15.80625		
Schwarz criterion	-14.9143	-15.20404			-15.76471	-15.7651		
Hannan-Quinn criter.	-14.9401	-15.22981			-15.79049	-15.79087		

\* indicates significance at 1%

## Exhibit 6

### Summary of Pairwise Estimates for Unidirectional Volatility Spillover from DJI (US) to ASXAO (Australia)

$\beta_{12}$  denotes volatility transmission from DJI to ASXAO.

<b>DJI and ASXAO</b>				
	<b>Coefficient</b>	<b>Std. Error</b>	<b>Z-Statistic</b>	<b>P-Val.</b>
$\mu_{11}$	0.0003	0.0003	0.9870	0.3236
$\mu_{22}$	0.0003	0.0002	1.2907	0.1968
$\Omega_{11}$	0.0023	0.0003	7.4825	0.00*
$\Omega_{12}$	0.0005	0.0003	1.8353	0.0665
$\Omega_{22}$	0.0013	0.0002	6.3192	0.00*
$\alpha_{11}$	0.2441	0.0177	13.7548	0.00*
$\alpha_{12}$	-0.0603	0.0137	-4.3942	0.00*
$\alpha_{22}$	0.3065	0.0207	14.8242	0.00*
$\beta_{11}$	0.9530	0.0072	131.9807	0.00*
$\beta_{12}$	0.0201	0.0062	3.2674	0.0011*
$\beta_{22}$	0.9303	0.0103	90.6807	0.00*
<b>Log LL</b>	9273.725			
<b>Ave. Log LL</b>	6.619361			
<b>AIC</b>	-13.22302			
<b>Schwarz criterion</b>	-13.18184			
<b>Hannan-Quinn criter.</b>	-13.20763			

$\beta_{12}$  denotes volatility transmission from DJI to ABI

<b>DJI and ABI</b>				
	<b>Coefficient</b>	<b>Std. Error</b>	<b>Z-Statistic</b>	<b>P-Val.</b>
$\mu_{11}$	0.0004	0.0003	1.2580	0.2084
$\mu_{22}$	0.0002	0.0001	2.7216	0.0065*
$\Omega_{11}$	0.0019	0.0003	6.7094	0.00*
$\Omega_{12}$	0.0002	0.0002	1.3787	0.1680
$\Omega_{22}$	0.0010	0.0001	8.9249	0.00*
$\alpha_{11}$	0.2494	0.0181	13.7784	0.00*
$\alpha_{12}$	0.0033	0.0066	0.4991	0.6177
$\alpha_{22}$	0.2777	0.0163	17.0565	0.00*
$\beta_{11}$	0.9576	0.0066	145.2375	0.00*
$\beta_{12}$	-0.0080	0.0030	-2.6675	0.0076*
$\beta_{22}$	0.8879	0.0202	43.9753	0.00*
<b>Log LL</b>	10401.11			
<b>Ave. Log LL</b>	7.424065			
<b>AIC</b>	-14.83243			
<b>Schwarz criterion</b>	-14.79125			
<b>Hannan-Quinn criter.</b>	-14.81703			

\* indicates significance at 1%

## Exhibit 7

### Summary of Pairwise Estimates for Unidirectional Volatility Spillover from DJCI(US) to Australia

$\beta_{12}$  denotes volatility transmission from DJCI to ABI.

<b>DJCI and ABI</b>				
	<b>Coefficient</b>	<b>Std. Error</b>	<b>Z-Statistic</b>	<b>P-Val.</b>
$\mu_{11}$	0.0002	0.0001	2.6745	0.0075*
$\mu_{22}$	0.0002	0.0001	2.9153	0.0036*
$\Omega_{11}$	0.0024	0.0001	29.5791	0.00*
$\Omega_{12}$	0.0000	0.0002	-0.2490	0.8033
$\Omega_{22}$	0.0000	0.0133	-0.0004	0.9997
$\alpha_{11}$	0.4426	0.0276	16.0616	0.00*
$\alpha_{12}$	-0.0851	0.0417	-2.0406	0.0413
$\alpha_{22}$	0.2661	0.0158	16.8288	0.00*
$\beta_{11}$	0.1434	0.1671	0.8578	0.3910
$\beta_{12}$	0.3729	0.1195	3.1196	0.0018*
$\beta_{22}$	0.8974	0.0205	43.7394	0.00*
<b>Log LL</b>	12485.949			
<b>Ave. Log LL</b>	8.9121694			
<b>AIC</b>	-17.8086			
<b>Schwarz criterion</b>	-17.7675			
<b>Hannan-Quinn criter.</b>	-17.7932			

$\beta_{12}$  denotes volatility transmission from DJCI to ABI.

<b>DJCI and ASXAO</b>				
	<b>Coefficient</b>	<b>Std. Error</b>	<b>Z-Statistic</b>	<b>P-Val.</b>
$\mu_{11}$	0.0002	0.0001	2.1352	0.0327
$\mu_{22}$	0.0003	0.0002	1.7430	0.0813
$\Omega_{11}$	0.0005	0.0001	6.9286	0.00*
$\Omega_{12}$	-0.0002	0.0004	-0.4507	0.6522
$\Omega_{22}$	0.0015	0.0003	5.2113	0.00*
$\alpha_{11}$	0.1966	0.0138	14.2367	0.00*
$\alpha_{12}$	-0.1692	0.0683	-2.4762	0.0133
$\alpha_{22}$	0.2946	0.0250	11.7945	0.00*
$\beta_{11}$	0.9663	0.0060	159.7531	0.00*
$\beta_{12}$	0.0466	0.0368	1.2658	0.2056
$\beta_{22}$	0.9342	0.0137	68.4297	0.00*
<b>Log LL</b>	11202.46			
<b>Ave. Log LL</b>	7.996044			
<b>AIC</b>	-15.97638			
<b>Schwarz criterion</b>	-15.9352			
<b>Hannan-Quinn criter.</b>	-15.96099			

\* indicates significance at 1%