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A Multiscale Analysis of Stock Return Co-movements and Spillovers: Evidence from Pacific Developed Markets

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HIGHLIGHTS

- Diversification benefits in Pacific developed markets are limited due to higher degrees of integration.
- Pacific developed markets co-move strongly during the periods of financial crisis.
- Higher degree of volatility spillover is observed during financial crisis.

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ABSTRACT

In this paper we examine the stock market co-movement and volatility spillover dynamics in the Pacific developed markets for a period spanning over January 05, 2001 to January 09, 2018. We employ wavelet-based techniques to study the multiscale co-movement dynamics of stock returns. Additionally, we also study the subtleties of volatility spillover of returns among the sample countries. We find that: (a) diversification benefits in these markets are limited due to higher degrees of integration, (b) Pacific developed markets co-move strongly during the periods of financial crisis (i.e. the contagion hypothesis) and (c) higher degree of volatility spills during financial crisis. We believe our study holds significance in the perspective of international portfolio diversification.

1. Introduction

This paper is a pursuit to: (a) validate co-movements among returns of the stock markets and (b) assess volatility spillovers at different time-scales with reference to recent time frame in the Pacific region. The objective of the paper expands to the study of benefits that may be achieved through portfolio diversification owing to the information of such co-movements and spillovers over different time horizons. Fragmentation of time into higher and lower frequencies enables speculation opportunities in between timescales. In a frictionless global scenario, movement in the index prices reveals the impact of information mediation. Correlation between markets confirms the international asset pricing, information spillover and international arbitrage theory. Based on the compliance of movement among the markets it is possible to map strategies for asset allocation and averaging returns [1–6].

Fundamentals underlying co-movement have led to the development of models over time by researchers in this field. Barberis and Shleifer [7] emphasized on the investor's discretion to classify assets on the basis of market-capitalization values, industry, or junk bonds. Coordination among such investor class to demand or withdraw affects the asset's return. The *habit view* approach [7] promulgate that there are specific factors like transaction costs, information awareness, risk aversion, or liquidity that drives the co-movement pattern in returns of such subset of assets as chosen by the investors. The *knowledge diffusion view*, on the other hand, states that return of stocks co-move depending on the time lag in transmission of news. Barberis *et al*., [8] proves that stocks in a particular index co-move with stocks in the same index. Correlated trading strategies of investors cause co-movement of the stocks with similar book-to-market ratios [9]. From the viewpoint of institutional investors, market co-movements may also be attributed to the preference of indices; an investor opts to invest in [10].

Hakkio [11] uses Monte Carlo simulation to show how use of frequently sampled data lead to apparent results which have less significance in reality and co-integration can only be inferred in the long run relationship among the markets. In an other endeavor, Panton *et al.,* [12] applies basic cophenetic correlation between sequential dendrogram to delve into the similarity of twelve internationals stock markets. The results suggest a strong similarity between United States (US) and Canada. However, the ties of Australia and Italy with other countries were detected noticeably low. It has been substantiated that the market correlation rises during times of high volatility especially during crisis phase [13–15]. A rise in cross correlation among the markets leads to excess co-movement or mispricing. Justifications for such are aplenty which usually extends to information constraints [16], trading strategies [17] or sunspot equilibria [18]. Financial integration is a precursor to financial stability. Integration among the markets provides benefits of diversifying risk, efficiently allocating capital and absorbing shocks. But on the drawbacks, high financial integration can spread shocks of a particular market to another, leading financial contagion [19].

In this endeavor, the multiscale co-movement of returns and spillover among the Pacific developed countries (Australia, Hong Kong, Japan, New Zealand and Singapore) is highlighted. Over the recent years, the free trade agreements among these countries have considerably facilitated flow of trade and commercial activities.[1] The cross-border

[1] The enactments of Free Trade Agreements (FTAs) among the sample countries have facilitated the flow of trade with ease. For detailed statistics and facts refer some of the following links:
(a)http://dfat.gov.au/trade/agreements/a-hkfta/Pages/default.aspx,
(b)http://dfat.gov.au/trade/agreements/jaepa/Pages/japan-australia-economic-partnership-agreement.aspx,
(c)https://www.mfat.govt.nz/en/trade/free-trade-agreements/free-trade-agreements-in-force/aanzfta-asean-australia-new-zealand-fta/,

movement of goods and has been propounded as a causal variable to lead co-movements in stock markets by past literature [20]. Though using the theoretical framework of economic integration, stock market co-movement may be assumed among these countries. However, literature focusing upon stock market co-movement and spillover among these countries in a time-frequency domain is limited. Thus, this study attempts to capture (a) level of regional integration, (b) the phenomenon of contagion and finally, (c) spillover of returns and volatility. In analyzing the data the paper adopts a multiscale framework on account of multiscale features of times series data [21]. The Wavelet-based methods, in particular, have been employed which is advantageous over the traditional econometric techniques to analyze the data in time-frequency domain [3,22–28]. Since, the emergence of *Econophysics* [29] as a prominent interface of application of scientific techniques (predominantly of Physics discipline) to solve economic problems, the use of methods such as Wavelets has gained considerable impetus, refer [2,27,30–39] for some contemporary literature on allied domain.

We report that the diversification benefits in these markets are limited since evidences of higher market integration are clearly evident. Additionally, we also document the indication of contagion and volatility spills during GFC. Nevertheless, the country pairs in which lower correlations are observed may serve as suitable destinations for cross diversifications. The rest of the paper is structured as follows: Section 2 briefly describes the methodology applied to estimate the results. Section 3 concisely explains the data. The main results are set out in Section 4. Section 5 concludes.

2. Estimation methodology

In this segment, we briefly discuss the methodology used in the study. We estimate our results using a wavelet-based methodological framework, as outlined by previous literature [3,23,25,26,33,35,40–45]. Section 2.1 describes the methodological approach to gauge degree of market integration. Section 2.2 discusses the method used to capture the contagion hypothesis. Finally, Section 2.3 relates to the aspect of spillover of returns.

2. 1. Market Integration

In order to asses the market integration we apply the wavelet correlation, wavelet multiple correlation and wavelet cross-correlation techniques [35].

Assume that $[x(t)]$ and $[y(t)]$ be any two time series with wavelet variances $Var(w_{rst})$ and $Var(\widetilde{w}_{rst})$, respectively, and wavelet covariance $Cov(w_{rst}, \widetilde{w}_{rst})$. The maximum overlap discrete wavelet transform (MODWT) estimator of the wavelet correlation can be written as follows:

$$\rho_{xy}(\lambda_s) = \frac{Cov(w_{rst}, \widetilde{w}_{rst})}{\sqrt{Var(w_{rst})Var(\widetilde{w}_{rst})}} \quad (1)$$

(d)http://dfat.gov.au/trade/agreements/safta/Pages/singapore-australia-fta.aspx, all accessed on September 4, 2017.

We use the Daubechies least asymmetric wavelet filter of length 8 to decompose the time series into six components D_1 to D_6 with respect to 'days' as the time frequency (refer Table 1 for interpretations of scales).

With respect to the time series $[x(t)]$, the wavelet multiple correlation can be written as:

$$\phi x(\lambda_s) = \frac{Cov(w_{rst}, \tilde{w}_{rst})}{\sqrt{Var(w_{rst})Var(\tilde{w}_{rst})}} \quad (2)$$

where w_{st} represents the scale of wavelet coefficient λ_j derived from the $x(rt)$ process based on MODWT.

Similarly, the wavelet multiple cross-correlation with respect to the time series $[x(t)]$ can be written as:

$$\phi x(\lambda_s) = \frac{Cov(w_{rst}, \tilde{w}_{rst+l})}{\sqrt{Var(w_{rst})Var(\tilde{w}_{rst+l})}}\,. \quad (3)$$

2. 2. Contagion

In order to exhibit the evolution of correlation patters across time and frequency Wavelet Local Multiple Correlation (WLMC) technique as recently suggested by Fernández-Macho [44] is adopted. The WLMC technique takes into consideration multiple time series in a single Continuous Wavelet Transform (CWT) framework. Thus, the co-movement dynamics of multivariate time series can be taken into account in a single map.

The WLMC is obtained by applying Maximum Overlap Discrete Wavelet Transform (MODWT) of J^{th} order to each of the univariate time series under consideration.[2] We obtain length-T vectors of MODWT coefficients from J as $\tilde{W} = \{\tilde{W}_{j0} \ldots \tilde{W}_{j,T-1}\}$, for $j = 1 \ldots J$. The consistent estimator MODWT-based WLC is given as:

$$\tilde{\varphi}X, s(\tau_j) = \sqrt{1 - \frac{1}{\max diag \tilde{P}_{j,s}^{-1}}} = Corr(\theta(t-s)^{1/2}\tilde{w}_{ijt}, \theta(t-s)^{1/2}\hat{\tilde{w}}_{ijt})$$

$$= \frac{Cov(\theta(t-s)^{1/2}\tilde{w}_{ijt}, \theta(t-s)^{1/2}\hat{\tilde{w}}_{ijt})}{\sqrt{Var(\theta(t-s)^{1/2}\tilde{w}_{ijt})Var(\theta(t-s)^{1/2}\hat{\tilde{w}}_{ijt})}}, s = 1 \ldots T,. \quad (4)$$

where $P_{j,s}$ represent $(n \times n)$ weighted correlation matrix of W_{jt} with corresponding weights of $\theta(t-s)$. The operator that selects the largest element in the argument diagonal is

[2] For parsimony, the methodology section is explained in brief. For a detailed discussion and explanation readers are requested to refer Fernández-Macho [35,44].

represented by $\max diag(.)$. The regression coefficient of determination is indicated by $\varphi X, s$ with respective scale (τ_j).

2. 3. Volatility Spillover

In order to compute the volatility, we apply a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which can be expressed as below:

$$y_t = C + \varepsilon_t$$
$$\sigma_t^2 = A_1 + A_2\sigma_{t-1}^2 + A_3\varepsilon_{t-1}^2 \tag{5}$$

We measure the spillover index by applying the methodology of Diebold and Yilmaz [46,47]. Let,

$$X_t = C_1X_{t-1} + C_2X_{t-2} + \cdots + C_qX_{t-q} + \epsilon_t \tag{6}$$

denotes the $VAR(q)$ model in which ϵ_t are *i.i.d.* shocks, and C_q is the q-th coefficient matrix. The moving average representation of X_t is given as follows:

$$X_t = \epsilon_t + M_1X_{t-1} + M_2X_{t-2} + \cdots \tag{7}$$

Let, the forecast at h-step ahead of t is denoted by $P(X_{t+h}|X_t, X_{t-1}, \ldots)$. Then the measure of spillover can be defined as follows:

$$X_{t+h} - P(X_{t+h}|X_t, X_{t-1}, \ldots) = \epsilon_t + M_1\epsilon_{t+h-1} + M_2\epsilon_{t+h-2} + \cdots + M_{h-1}\epsilon_{t+1}. \tag{8}$$

The covariance matrix of the forecast error can be written as:

$$\Sigma_{\epsilon,u} = \sum_{u=0}^{h-1} M_u \Sigma_\epsilon M_u', \tag{9}$$

where Σ_ϵ denotes the covariance matrix of M_0 and ϵ.

Let, L denotes the lower triangular Cholesky decomposition of Σ_ϵ. Then the error variance forecast of the r-th variable can be defined as $\sum_{s=1}^{N}(M_hL)_{rs}^2$. So, $\sum_{u=0}^{h-1}(M_hL)_{rs}^2$ may be considered as the contribution of the shock from the error variance forecast of the variable r and s. Accordingly, the spillover index (SI) can be written as:

$$SI = \frac{1}{N}\sum_{r=1}^{N}\frac{\sum_{r\neq s}\sum_{u=0}^{h-1}(M_hL)_{rs}^2}{\sum_{u=0}^{h-1}(M_h\Sigma_\epsilon M_h')_{rr}} \times 100 \tag{10}$$

Table 1. Time interpretation of different frequencies

Details	*Wavelet Scales*	*Periods*	*Frequency Bands*
D_1	1	2-4 weeks	Up to 1 Month
D_2	2	4-8 weeks	1-2 Months
D_3	4	8-16 weeks	2-4 Months
D_4	8	16-32 weeks	4-8 Months
D_5	16	32-64 weeks	8-16 Months
D_6	32	64-128 weeks	16-32 Months

3. Data and statistical properties

We consider the time-series data for equity prices of five developed markets in Pacific region. The selection of the sample countries is based on the Morgan Stanley Capital International (MSCI) classification. The constituent countries and respective stock indices with a brief description is presented as below in Table 2:

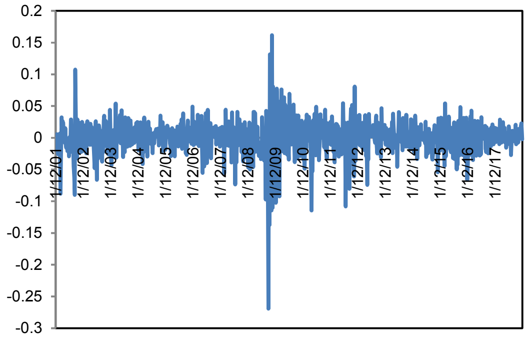
Table 2. Description of stock indices

Country	Index Symbol	Description
Australia	S&P/ASX200	This index is a measure 200 largest stocks listed on Australian Stock Exchange and widely considered as a prominent benchmark index of Australia. The index was launched in April 2000.
Hong Kong	HSI	The Hang Seng Index represents the free-float capitalization-weighted index of selected companies, which are divided in four sub-indices: Commerce and Industry, Finance, Utilities and Property in the Stock Exchange of Hong Kong. This index was developed as on July 31, 1964 with a base level of 100.
Japan	NKY	The Nikkei-225 is a price-weighted average index of top 225 Japanese stocks listed in First Section of the Tokyo Stock Exchange. On May 16, 1949, the average price of this index was first published.
New Zealand	S&P/NZX50	This is a modified market capitalization weighted index that represents the top 50 stocks listed on the New Zealand Exchange Limited (NZEL) by free-float adjusted market capitalization.
Singapore	FSSTI	The Straits Times Index (STI) is the globally recognized market barometer and benchmark index of Singapore. This index measures the performance of top 30 largest and most liquid stocks listed on Singapore Exchange. The index dates back to 1966.

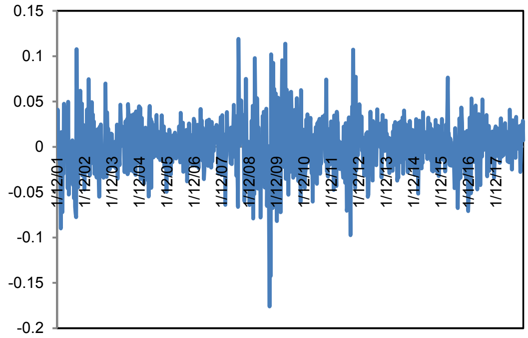
Note: The authors have compiled the table of description above, from: https://www.bloomberg.com/quote/, accessed as on July 17, 2017.

Our dataset spans over the period of January 05, 2001 to January 09, 2018 (889 observations). To avoid the problems of non-synchronous daily trading across different countries in the sample set, we consider weekly frequency of the data.[3] The equity prices are converted into returns by taking logged differences as: $R_t = (\ln(P_t) - \ln(P_{t-1}))$. The plots of logarithmic returns of equity indices are presented in Figure 1.

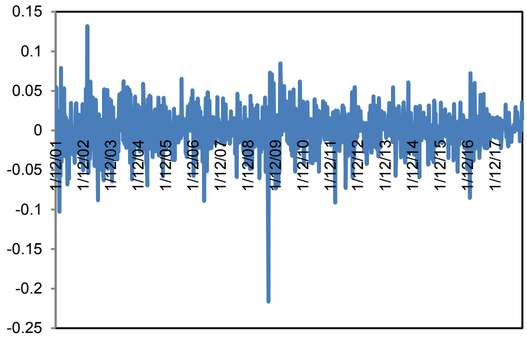
[3] Martens and Poon [57] states that the true correlations between markets may be underestimated if non-synchronous data is used. Thus, we use the weekly data to address this problem.



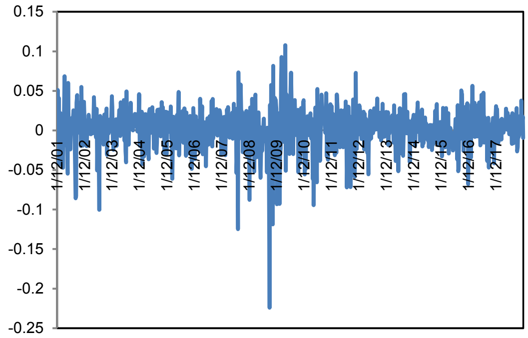
(a) Australia



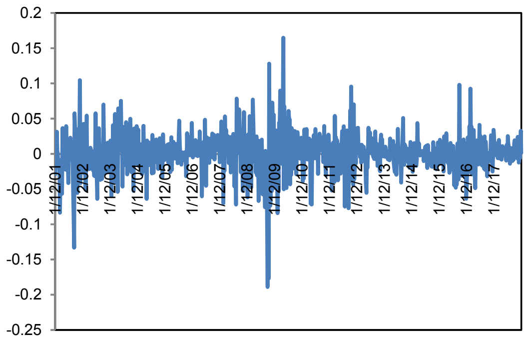
(b) Hong Kong



(c) Japan



(d) New Zealand



(e) Singapore

Figure 1. Logarithmic returns of equity indices

Table 2 reports the statistical properties for the logarithmic returns. The mean returns and standard deviation (SD) is annualized and the risk-return relationship is also mapped in Figure 2.[4] It can be easily observed that New Zealand outperforms all other stock markets in terms of returns and risk is relatively low. Australian market, on the other hand, yields the lowest returns.

Table 3. Statistical properties

[4] The calculations and plot for annualized returns and SD (risk) is performed using R package *PerformanceAnalytics*.

	Australia	Hong Kong	Japan	New Zealand	Singapore
Mean	-0.65%	1.78%	1.36%	10.61%	2.65%
SD	20.36%	21.40%	19.96%	19.07%	20.53%
Maximum	0.16	0.12	0.13	0.11	0.16
Minimum	-0.27	-0.18	-0.22	-0.22	-0.19
Skewness	-1.27	-0.24	-0.64	-1.33	-0.43
Kurtosis	15.61	5.73	7.94	11.08	9.29
JB	6123.60	285.16	965.50	2679.20	1489.40
LB Q-Stat.	22.83	8.24	8.95	10.01	16.18
	(0.01)	(0.61)	(0.53)	(0.44)	(0.09)
ADF	-31.96	-29.72	-30.98	-29.15	-28.35
PP	-31.94	-29.76	-30.97	-29.17	-28.47

Note: The critical value of Jarque-Bera (JB) test at 5% level is 5.99. Ljung-Box (LB) test is performed taking lag of 10, the LB *Q*-stats and the respective *p*-values (in parentheses) is reported. The z-statistics of ADF and PP, which stands for the Augmented Dickey-Fuller and Phillips-Perron tests for unit root, is reported.

The skewness coefficient is negative for all the markets, which indicates negative returns are more frequent than large positive returns. In other words, all the markets are more susceptible to realize negative returns on any event of economic downturn [48]. The kurtosis coefficient for all markets is positive and peaked than normal and hence leptokurtic. The investor community often appreciates a significant and positive kurtosis coefficient. The underlying reason being a higher probabilities of positive returns [48]. The returns series for all the assets clearly rejects the proposition of normality as reflected by the JB test results. The Ljung-Box Q-Statistic at order of lags 10 shows serial dependence for Australian and Singaporean markets. Finally, the ADF and PP results shows that all time series under consideration is stationary at 1% level of significance.

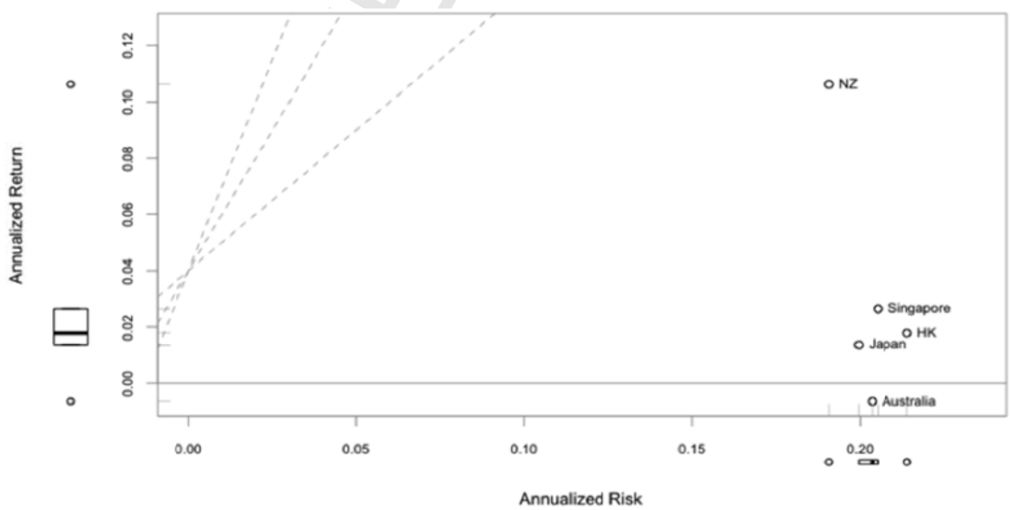


Figure 2. Annualized risk-return characteristics

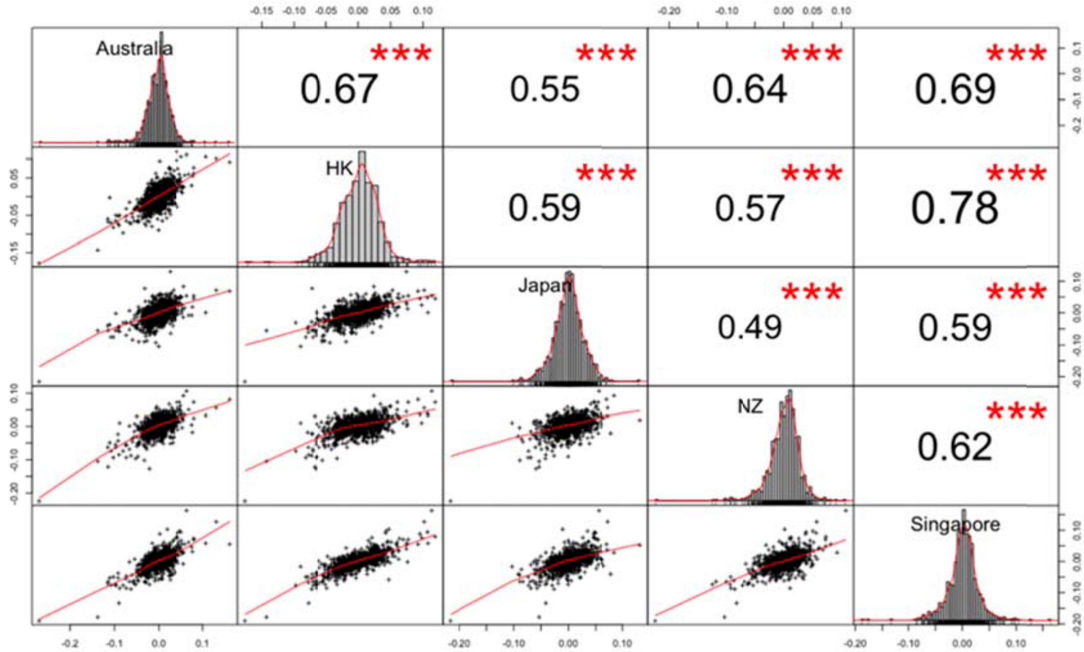
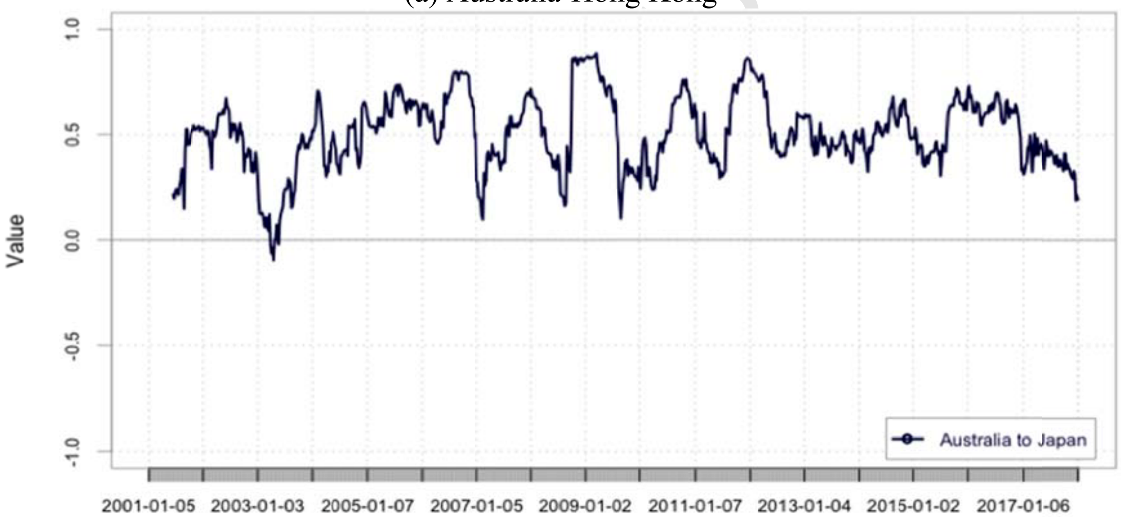


Figure 3. Scatter plots, histograms and Pearson correlation of index returns series
Note: *** Correlation is significant at the 0.01 level (2-tailed).

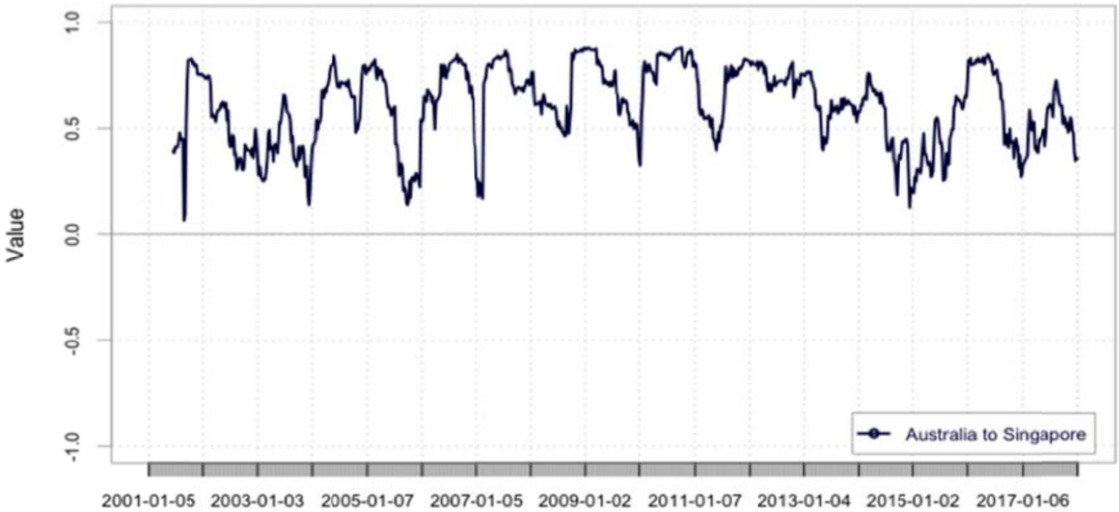
Figure 3 shows significant correlations between all the markets. The highest degree of correlation is observed between Hong Kong and Singapore (0.78), where the lowest is observed for the pair Japan and New Zealand (0.49). In addition, to the linear correlations, we also provide the pair-wise analysis of 12 weeks (3 months) rolling correlations among the concerned market set in Figure 4. As it can be observed that the correlations are time varying and oscillates across the timespan. Thus, the linear correlation coefficient may not represent the true correlation dynamics [49]. Further, a higher degree of correlation may also be observed around the period 0f 2008-09, which corresponds to the Global Financial Crisis (GFC). This phenomenon may be attributed to the contagion hypothesis [50].

(a) Australia-Hong Kong



(b) Australia-Japan

(c) Australia-New Zealand



(d) Australia-Singapore

(e) Hong Kong-Japan

(f) Hong Kong-New Zealand

(g) Hong Kong-Japan

(h) Japan-New Zealand

(i) Japan-Singapore

(j) New Zealand-Singapore

Figure 4. 12 weeks (3 months) rolling correlations

4. Results and Discussion

This section discusses the results in detail in accordance with our set objectives. In Section 4.1 we discuss the dynamics of market integration followed by Section 4.2 that describes the results of test for detection of contagion hypothesis. Finally, in Section 4.3 we report and interpret the results of spillover analysis.

4.1. Market Integration

In order to assess the degree of market, we first employ the pair-wise wavelet correlation analysis following previous studies [45,51], as presented in Figure 5. We find the evidence that Hong Kong and Singapore are most correlated markets with correlation coefficients ranging from 0.75 to 0.92 across the various wavelet scales. On the other hand, the pair of Japan and New Zealand is least correlated among the other pairs over the different time-frequencies. Based on the results, we construct diversification ranking of the market-pairs as exhibited in Table 4. It is clearly observable that the markets of Japan, New Zealand and Hong Kong depict lower degrees of correlation. Thus, these markets could be useful for diversifying the investments.

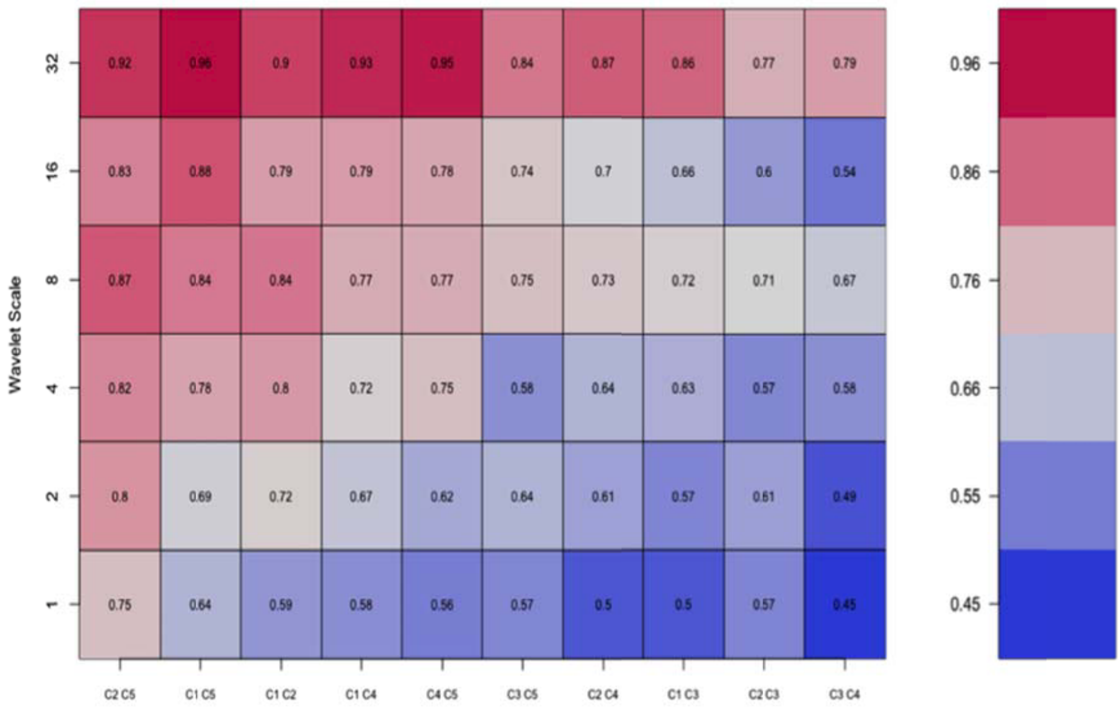


Figure 5. Wavelet correlation matrix

Note: C1: Australia, C2: Hong Kong, C3: Japan, C4: New Zealand, C5: Singapore

The x-axis shows the combinations for estimating wavelet correlation coefficients. The wavelet scales represented in the y-axis represent time-periods, which corresponds to 2^j, where superscript j represents the scale. The color bar on the right indicates the strength of correlation. (For interpretation of the references to colour in this figure legend, the readers are requested to refer the web version of the article.)

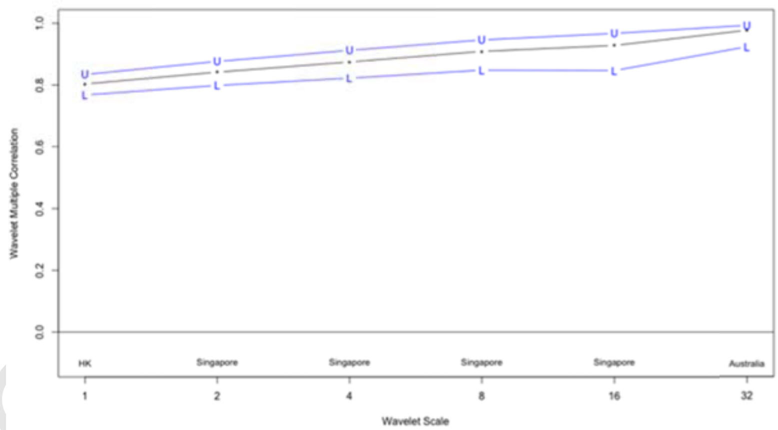


Figure 6. Wavelet multiple correlation for Pacific market returns

Note: The blue lines correspond to the upper and lower bounds of the 95% confidence interval.

Table 4. Rankings for correlation at different time scales

Rank	Up to 1 Month	1-2 Months	2-4 Months	4-8 Months	8-16 Months	16-32 Months
1	Japan-New Zealand (0.45)	Japan-New Zealand (0.49)	Hong Kong-Japan (0.57)	Japan-New Zealand (0.67)	Japan-New Zealand (0.54)	Hong Kong-Japan (0.77)
2	Australia-Japan (0.50)	Australia-Japan (0.57)	Japan-New Zealand (0.58)	Hong Kong-Japan (0.71)	Hong Kong-Japan (0.60)	Japan-New Zealand (0.79)
3	Hong Kong-New Zealand (0.50)	Hong Kong-Japan (0.61)	Japan-Singapore (0.58)	Australia-Japan (0.72)	Australia-Japan (0.66)	Japan-Singapore (0.84)
4	New Zealand-Singapore (0.56)	Hong Kong-New Zealand (0.61)	Australia-Japan (0.63)	Hong Kong-New Zealand (0.73)	Hong Kong-New Zealand (0.70)	Australia-Japan (0.86)
5	Hong Kong-Japan (0.57)	New Zealand-Singapore (0.62)	Hong Kong-New Zealand (0.64)	Japan-Singapore (0.75)	Japan-Singapore (0.74)	Hong Kong-New Zealand (0.87)
6	Japan-Singapore (0.57)	Japan-New Zealand (0.64)	Australia-New Zealand (0.72)	New Zealand-Singapore (0.77)	New Zealand-Singapore (0.78)	Australia-Hong Kong (0.90)
7	Australia-New Zealand (0.58)	Australia-New Zealand (0.67)	New Zealand-Singapore (0.75)	Australia-New Zealand (0.77)	Australia-Hong Kong (0.79)	Hong Kong-Singapore (0.92)
8	Australia-Hong Kong (0.59)	Australia- Singapore (0.69)	Australia- Singapore (0.78)	Australia-Hong Kong (0.84)	Australia-New Zealand (0.79)	Australia-New Zealand (0.93)
9	Australia- Singapore (0.64)	Australia-Hong Kong (0.72)	Australia-Hong Kong (0.80)	Australia- Singapore (0.84)	Hong Kong-Singapore (0.83)	New Zealand-Singapore (0.95)
10	Hong Kong-Singapore (0.75)	Hong Kong-Singapore (0.80)	Hong Kong-Singapore (0.82)	Hong Kong-Singapore (0.87)	Australia- Singapore (0.88)	Australia- Singapore (0.96)

Note: The ranking is based lowest to highest degree of correlation i.e. rank 1 for lowest and rank 10 for highest. In the case of tie between two correlation coefficients in the same scale, the country with lower correlation coefficient in the subsequent scale is assigned higher rank. The correlation coefficients are indicated in parentheses.

In addition to the pair-wise wavelet correlation, we also perform wavelet multiple correlation to assess the degree of regional integration, in congruence with earlier literature [35,49,45,52]. The figure for wavelet multiple correlation is presented in Figure 6. As it can be clearly observed that at lowest scale the degree of integration is a 0.80 and that increase monotonically till the highest scale. This result indicate an impending state of perfect integration in Pacific developed markets. Thus, the phenomenon of perfect integration limits arbitrage and portfolio diversification opportunities.

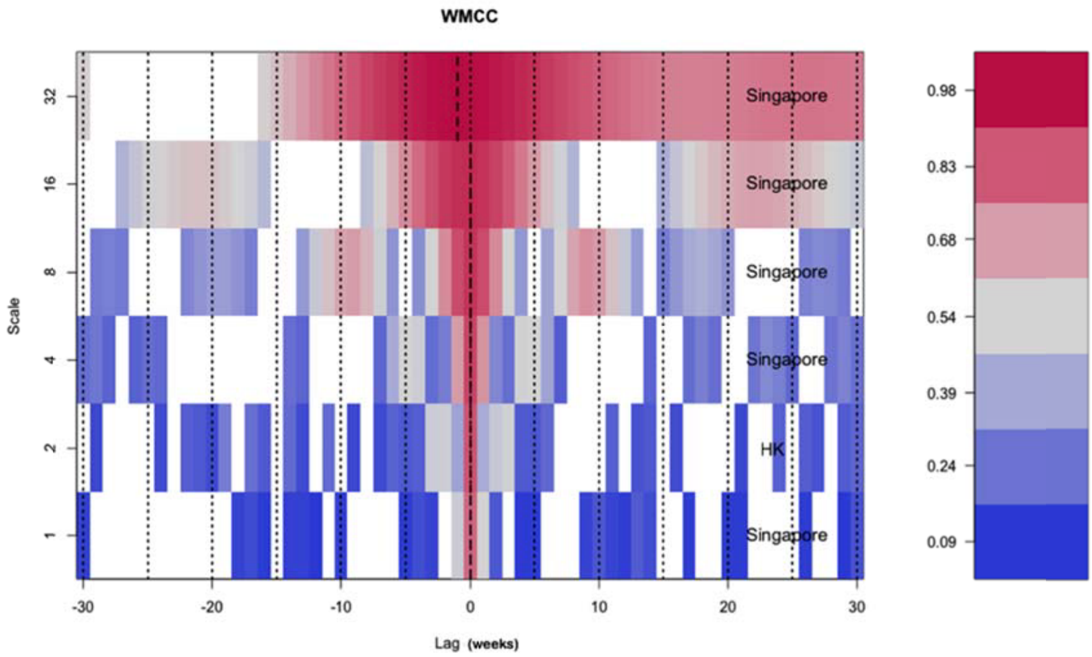


Figure 7. Wavelet multiple cross-correlation for Pacific market returns
Note: For each wavelet correlation the coefficients are within 95% confidence interval. The white areas indicate the zones where 95% interval spans zero. The vertical long-dashed lines indicate the localization of strongest wavelet correlation. The color bar on the right indicates the strength of correlation. (For interpretation of the references to colour in this figure legend, the readers are requested to refer the web version of the article.)

Figure 7 reports the result of wavelet multiple cross-correlations. The results suggest that Singapore statistically takes the lead among the developed markets of the Pacific at all the frequencies except for scale 2, which is lead by Hong Kong. Singaporean market thereby maximizes the multiple correlations against the linear combination of other countries. Minor inconsistencies between the markets eases out when the lags increase, caused majorly due heterogeneous investor diasporas. One of the underlying reasons that may be attributed to emergence of Singaporean markets as the potential leader could be its status of *'hub for Association of Southeast Asian Nations (ASEAN) companies'*.[5] The

[5] For a detailed report refer the following link: http://www.businesstimes.com.sg/companies-markets/asia-pacific-to-remain-most-active-region-for-new-ipos-as-singapore-retains-hub, accessed January 02, 2018.

ASEAN companies are recognized as major economic force and potential driver of global growth.[6]

4.2. Contagion

In this sub-section we examine the contagion hypothesis [44,50,43] among the Pacific developed markets. Forbes and Rigobon [50] purports that correlations in short-run intensifies during the periods of economic crisis. We intend to capture the dynamics of contagion in a wavelet-based framework using wavelet local multiple correlations technique proposed recently by Fernández-Macho [44].

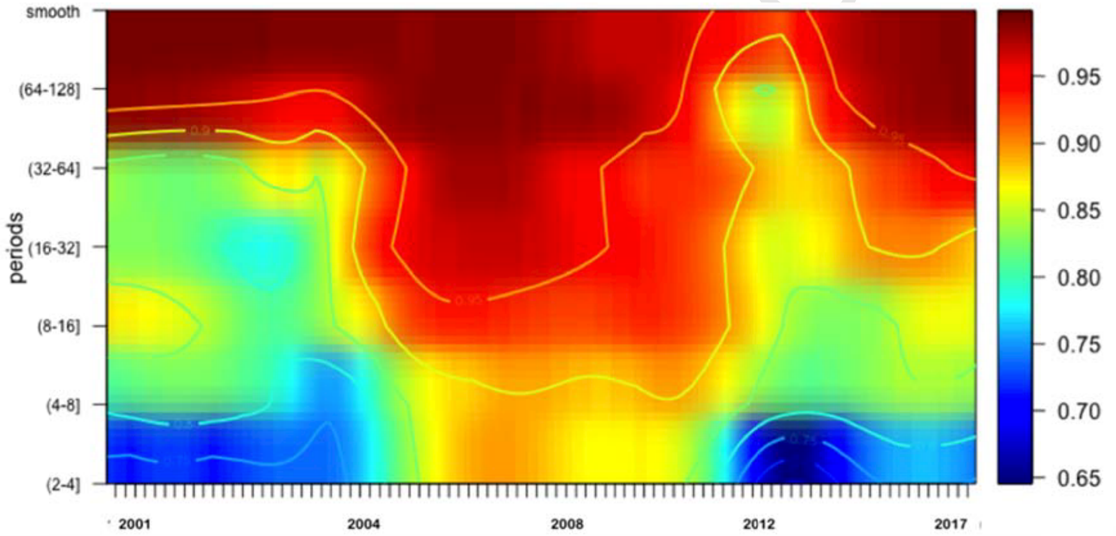


Figure 8. Wavelet local correlations
Note: The red (blue) colors signify region with high (low) coherency. The legend (on the right of the maps) shows the power of coherence coefficients. (For interpretation of the references to colour in this figure legend, the readers are requested to refer the web version of the article.)

The period of Global Financial Crisis (GFC) typically referred from September 2008 to March 2009 [53]. This was the period of global economic holocaust and phenomenon of contagion was prominent [44,54,55]. We find similar evidence in the case of the Pacific developed markets. As it can be observed that red and yellow zones melts down to high frequencies of 2-4 days. The local correlation increases up to the coefficient value of 0.90. Hence, we confirm the existence of contagion in the Pacific developed markets.

4.3. Volatility Spillover

The dynamics of spillover of volatility among the Pacific developed markets is studied in this sub-section. The relationship between contagion and volatility is evident in literature [56]. The earlier literature embraces common consensus that unanticipated shocks in the

[6] For a detailed report refer the following link: https://www.jpmorgan.com/country/US/EN/cib/investment-banking/trade-asean-future, accessed January 04, 2018.

stock markets lead to contagion [56]. Figure 9 shows a steep jump around the period of GFC, similar to the period in a state of contagion is depicted in Figure 8. For validation of our results we also test the level of volatility spillover among the sample markets using the framework suggested by Diebold and Yilmaz [46,47].

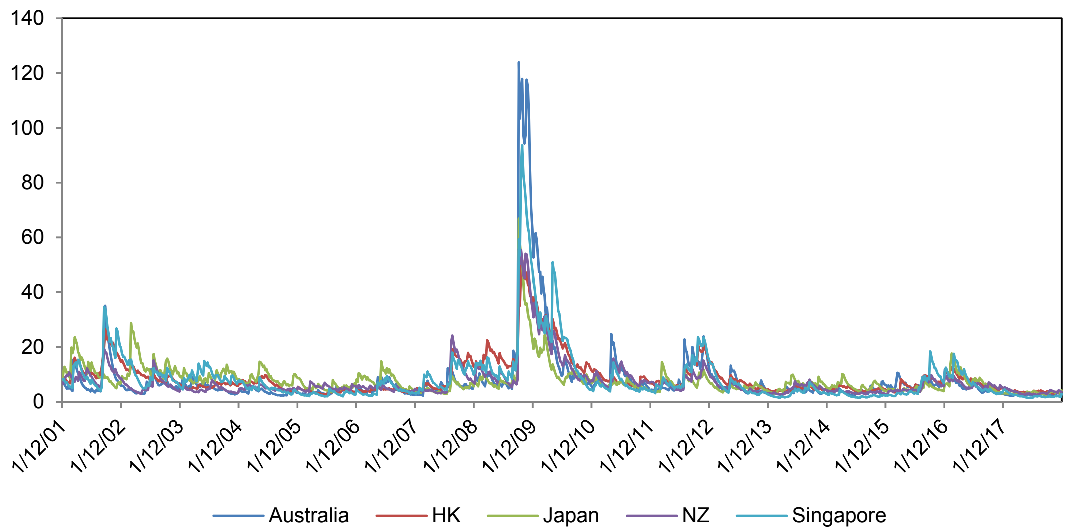


Figure 9. Volatility of returns

Table 5. Volatility spillover table

(a) Full-sample

	Australia	HK	Japan	NZ	Singapore	From Others
Australia	88.20	10.15	0.90	0.45	0.30	11.80
HK	88.00	10.29	1.07	0.38	0.27	89.71
Japan	86.65	10.99	1.85	0.31	0.21	98.15
NZ	84.85	11.53	3.21	0.22	0.19	99.78
Singapore	86.86	10.13	2.63	0.19	0.19	99.81
To Others	346.35	42.80	7.81	1.32	0.97	
Net	334.54	-46.92	-90.34	-98.45	-98.84	**SOI** =79.85

(b) Pre-GFC

	Australia	HK	Japan	NZ	Singapore	From Others
Australia	88.24	8.09	2.36	0.97	0.35	11.76
HK	88.00	8.13	2.76	0.81	0.30	91.87
Japan	86.37	8.29	4.50	0.62	0.22	95.50
NZ	83.89	8.17	7.34	0.41	0.19	99.59
Singapore	85.29	7.67	6.47	0.37	0.20	99.80
To Others	343.54	32.22	18.94	2.76	1.05	

Net	331.78	-59.65	-76.56	-96.83	-98.75	**SOI** =79.70

(c) During-GFC

	Australia	HK	Japan	NZ	Singapore	From Others
Australia	99.19	0.40	0.25	0.02	0.15	0.81
HK	98.94	0.74	0.17	0.02	0.13	99.26
Japan	99.04	0.63	0.18	0.01	0.13	99.82
NZ	98.97	0.64	0.25	0.01	0.13	99.99
Singapore	98.95	0.66	0.26	0.01	0.12	99.88
To Others	395.90	2.33	0.93	0.06	0.54	
Net	395.09	-96.93	-98.89	-99.93	-99.34	**SOI** =79.95

(d) Post-GFC

	Australia	HK	Japan	NZ	Singapore	From Others
Australia	94.12	4.82	0.40	0.23	0.33	5.78
HK	94.00	4.64	0.31	0.25	0.27	94.83
Japan	94.26	4.87	0.28	0.30	0.29	99.72
NZ	92.44	6.03	0.20	0.30	0.59	99.26
Singapore	92.82	6.11	0.18	0.31	0.58	99.42
To Others	373.52	21.83	1.09	1.09	1.48	
Net	367.74	-73.00	-98.63	-98.16	-97.95	**SOI** =79.80

Table 5 depicts the results of full-sample analysis of return spillover during the period of analysis. The specification of a lag structure for the vector auto regression (VAR) is necessary to calculate the spillover indices. In this paper, the lag order VAR considered for analysis is three. Table 5 summarizes the forecast error variances (across different permutations) that each of the constituent countries in Pacific region transmits (to) and receives (from) the other member countries. Further, it also exhibits the total forecast error variances that one country emits to all other countries (to others), in addition the component of variance forecast error that a country receives from other countries is also represented (from others). The net difference of spillovers between *to others* and *from others* is given by the row headed as *'Net'*. Spillover Index (SOI) indicates the overall measure of spillover across the given permutations of countries.

The period of study is divided into three sub-samples i.e. pre, during and post-GFC periods.[7] We first report the results for the full sample in Table 5(a), the pre, during and post-GFC results are reported in Table 5(b), (c), (d) respectively. The SOI clearly indicates that the spillover level enhances during the GFC period, which could be one of the possible reasons to spur the contagious behavior among the sample countries. In addition, we also report that Australia is the emitter of volatility spills to other markets for all the three sub-sample periods.

[7] We follow Samarakoon [53] for referring the period of GFC i.e. September 2008 to March 2009.

5. Conclusions

This paper examine the phenomenon of the regional stock market integration in the Pacific developed markets. The results of the study have shown that there exists a higher degree of integration, which depict a state of impending perfect market integration with Singapore as potential market leader. In addition, the phenomenon of contagion is also found prevalent among the sample countries. Further, we also report the evidence of high volatility spills during the GFC and Australia is the major emitter of volatility spills.

Overall, the results suggest that the diversification benefits in Pacific markets are limited since evidences of higher market integration are clearly evident. However, the country pairs in which lower correlations are observed may serve as suitable destinations for cross diversifications. The results of this study is relevant for investors in Pacific markets who intends to diversify the investment portfolio regionally in addition to the transnational investors who consider stock markets in this region for inclusion in the investment portfolio in order to diversify portfolio.

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Highlights

•Diversification benefits in Pacific developed markets are limited due to higher degrees of integration.

•Pacific developed markets co-move strongly during the periods of financial crisis.

•Higher degree of volatility spillover is observed during financial crisis.