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Abstract

This paper examines financial linkages among Asia-Pacific stock markets and those between these markets and other global markets. By studying the mean and tail dependences of the 37 stock market indices, we find that while Asia-Pacific stock markets is mainly driven by shocks within the Asia-Pacific region under mean dependence, shocks from regional and non-regional markets are equally considerable to Asia Pacific in the tail. In particular, shocks from Latin America and EMEA have increased notably after the taper tantrum. Moreover, we find that price-earnings ratios can explain the sensitivity of individual Asia-Pacific economy to shocks under the tail dependence, but does not seem to offer any explanatory power under mean dependence.

Keywords: Spillovers; tail risk; vector autoregression; emerging markets
JEL classification: C32; G15

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1. Introduction

Partly due to the spillover from the quantitative easing programs adopted by the US Federal Reserves, stock prices in the Asia-Pacific region have risen considerably since 2009.(Figure 1) [1]. Accompanied with this bull market run, however, there were two notable stock market corrections in 2013 and 2015, with prices in some economies falling over 20% in a week. With these significant downside risks as background, a natural question is "what is the major source of contagion to Asia-Pacific stock markets during these sell-offs?" Answers to this question are important for policymakers to avoid international financial contagion and to preserve financial stability because shocks from foreign stock markets could have ramifications for domestic stock markets, and in turn, could affect domestic currency markets and ultimately sovereign creditworthiness.[2]

Before answering this question, it is necessary to identify an appropriate measure of financial spillovers. The extant empirical literature offers extensive evidence regarding spillovers between cross-country stock market returns. [3] However, many of them have overwhelmingly focused on evaluating the mean relationship between stock market returns (namely, mean dependence). This kind of analysis reflects mostly the risk during tranquil periods which could underestimate the real effects of an international shock in times of financial crisis. A more relevant analysis of contagion should evaluate relationships among extremely negative returns (namely, tail dependence) which are more likely associated with bearish markets, periods of crises and financial distress.

In this paper, we examine the financial linkages of Asia-Pacific stock markets within the region and with other global markets by studying the mean and tail dependences of the stock market prices. Through estimating these linkages, we could identify major sources of risk spillovers at the mean (namely, mean risk spillovers) and at the tail (namely, tail risk spillovers) respectively to the region. We contribute to the studies of contagion and cross-border spillovers by using multivariate quantile

[1] See Chen et al. (2016) and the references cited therein for a recent discussion on the spillovers generated by the US quantitative easing on other economies.

[2] Spillovers from equity market are important for the financial stability. Park and Mercado (2014) find that stress in stock markets could ripple through the whole financial system during financial crisis. Reboredo et al. (2016) also find that downside risk spillovers from stock prices to exchange rates could be substantial for emerging market economies.

[3] See Forbes (2013) for a recent survey on the contagion and spillovers between cross-country stock market returns.

analysis to address the concerns over underestimating spillover impacts on the region in earlier studies.

We show that mean and tail dependences of stock market prices exhibit a distinct pattern of risk attribution. While the mean risk spillovers to Asia-Pacific stock markets is mainly driven by shocks within the Asia-Pacific region, shocks from regional and non-regional markets are equally considerable to Asia Pacific in the tail risk spillovers. Specifically, shocks from Latin America and Europe, Middle East and Africa (EMEA) have become more prominent after the taper tantrum in May 2013. One interesting finding is that price-earnings (PE) ratios, a common indicator for evaluating the risk of overvaluation, can explain the sensitivity of individual Asia-Pacific economy to shocks under the tail dependence, but does not seem to offer any explanatory power under mean dependence.

The rest of the paper is organised as follows. First, we discuss our empirical model in this analysis. We then describe the sample data used in estimation. The empirical results are presented in the next section. Finally, we outline the conclusions that can be drawn from this study.

2. Empirical model

Quantile vector autoregressive model

We first use a quantile vector autoregressive (QVAR) model to capture dynamics of 37 equity market returns. The general idea behind the QVAR model is that the model specifies quantiles of the distribution of a time series, x_{it} , to depend on its own lags and on the lags of covariates of interest. In our case, the extremely negative returns are considered to potentially depend on its lagged returns and lagged returns of other stock markets in the specification.

Basically, the QVAR specification is same as the following P-order VAR model:

$$x_t = \sum_{i=1}^{p} \Theta_i x_{t-1} + \Phi w_t + \varepsilon_t \tag{1}$$

where $x_t = (x_{1t}, \ldots, x_{Nt})$is a $N \times 1$ vector of endogenous variables, w_t is a $M \times 1$ vector of exogenous variables, $\Theta_i, i = 1,2, \ldots p$ and Φ are $N \times N$ and $N \times M$ coefficient matrices and $\varepsilon_t \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances.

Unlike the conventional VAR model, the QVAR model is estimated by solving the following objective function:

$$\hat{\alpha}(\tau) = \arg \min_{\Theta,\Phi} \sum_{t=p+1}^{N} \rho_\tau \left(x_t - \sum_{i=1}^{p} \Theta_i x_{t-1} - \Phi w_t \right) \quad (2)$$

Where $\rho_\tau(z) = z(\tau - I(z < 0))$ as given by Koenker and Bassett (1978) and $I(*)$ is an indicator function. The estimated coefficients and residuals are used as inputs to computations of spillover measures discussed in the next sub-section.

Generalised forecasting variance decomposition

Based on inputs from the previous section, we then employ the Diebold and Yilmaz (2009, 2012)'s approach to compute financial linkages between stock market returns. These linkages are measured by generalised forecast error variance decomposition (GFVD) of an underlying VAR model. [4] They explicitly track spillovers at all endogenous variables, from pairwise to system-wide, in a coherent and mutually consistent way. This is in contrast to conventional spillover measures derived from correlation and covariance models that can only measure the pairwise associations among the variables of interest. [5]

Based on coefficients of QVAR and the residuals obtained from Equation (2), GFVD is computed as follows. Assuming Eq. (1) is covariance-stationary, we can rewrite its moving average representation as:

$$x_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-i} + \sum_{i=0}^{\infty} Q_i \, w_{t-i} \quad (3)$$

[4] As suggested by Koop et al. (1996) and Pesaran and Shin (1988), the variance decomposition (VD) of VARs using GFVD is invariant to the variable ordering, as opposed to the traditionally used Choleski decomposition.

[5] Given this desirable feature, the method is widely applied in many empirical studies in the context of contagion (for example, Alter and Beyer (2014), Claeys and Vasicek (2014), Apostolaskis and Papadopoulos (2014), Louzis (2015), Liow (2015)).

Where A_i are derived by the recursion $A_i = \Theta_1 A_{i-1} + \cdots + \Theta_p A_{i-p}$ with A_0 being an $N \times N$ identity matrix with $A_i < 0$ for $i < 0$, and $Q_i = A_i \Phi$. The H-step-ahead GFVD is then given by:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{4}$$

Where σ_{jj} is the standard deviation of the error term for the j^{th}equation and e_i is a selection vector, with one as the i^{th} element and zeros otherwise. When considering $i \neq j, (for\ i, j = 1, \ldots, N)$, this GFVD is regarded as the "cross variance shares" that measures the fractions of the H-step-ahead error variances in forecasting x_{it} due to shocks originated from x_{jt}. It is also interpreted as the "spillovers" which measures the extent that the shocks originated from x_{jt} transmit to x_{it}. When considering $i = j$, the GFVD in Eq. (4) is regarded as the "own variance shares" which is the fractions of the H-step-ahead error variances in forecasting x_{it} due to shocks originated from itself.

Each entry of the variance decomposition matrix $\theta_{ij}(H)$ $(for\ i, j = 1, \ldots, N)$ is normalised by the row sum to yield:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{i=1}^{N} \theta_{ij}(H)} \tag{5}$$

and by construction $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$, and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$. This normalisation allow us to decompose the forecast error variance of the return of an asset i into the percentage of its own shock $\tilde{\theta}_{ii}$ and the percentages of shocks from other economies $\tilde{\theta}_{ij}$ $(for\ i, j = 1, \ldots, N, i \neq j)$, which facilitates easier identification of key shock origins and easier comparison among these shocks.

Using the normalised variance decomposition matrix, we can construct the total spillover index to capture the cross-asset or cross-market spillovers, which is defined as:

.
$$S(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \tag{6}$$

In other words, it is an average of all the normalised variance decompositions in the off-diagonal matrix that represents the average spillovers across all asset classes.

3. Data

We primarily measure the stock market spillovers among 13 Asia Pacific economies in this analysis. To make this assessment more comprehensive, we additionally include 24 stock market returns (i.e., 11 advanced economies, 8 emerging EMEA, and 5 Latin America) (Table 1) in the QVAR estimation.

Weekly returns are used to address the different time-zones problem given that the selected economies locate in different continents, and higher frequency data are too noisy and may generate distortion in the estimation distortion. [6] The final sample of 37 stock market returns covers a period from 2 January 2009 to 30 June 2016 and includes a total of 391 observations. Since several studies have identified a structural break at the episode of taper tantrum, [7] we divide the sample into two sub-periods: (1) 2 January 2009 to 24 May 2013 (defined as pre tapering period) and (2) 27 May 2013 to 30 June 2016 (defined as post tapering period).

All stock market data were obtained from Bloomberg. The stock indices are transformed into logarithmic returns by taking the first difference of natural logarithm. Specifically, the return $(R_{i,t})$ for market i in time t is defined as $R_{i,t} = [\ln(SI_{i,t}) - \ln(SI_{i,t-1})]$ where $SI_{i,t}$ is the stock index of market i.

In each QVAR specification, three exogenous variables are used to control for the effect of global factors. They are (i) the Chicago Board Options Exchange Standard & Poor's 500 Implied Volatility Index (VIX) which proxies for the global risk appetite; [8] (ii) the 10-year US Treasury term premium estimated by the Federal Bank of New York which proxies for the effect of unconventional monetary policies (UMP) adopted by the US Fed; [9] and the US dollar (DXY) index which controls for the effect

[6] We use the Friday closing prices in the estimation.

[7] Some examples include Aizenman et al. (2014), Fong et al. (2016), and Li et al. (2017).

[8] Forbes and Warnock (2012) argue VIX goes a long way in explaining the direction and movement of capital flows globally. Recent studies such as Bruno and Shin (2015) and Rey (2015) further argue VIX can be used to proxy for global liquidity conditions, with a declining VIX representing abundant global liquidity, and vice versa.

[9] As Bernanke (2013) argues, UMPs aim to lower the term premium and ease the boarder financial conditions. More details of the methodology for calculating the term premium can be found in Adrian et al. (2013).

of the USD appreciation. [10] VIX and DXY are downloaded from Bloomberg and the term premium is sourced from Federal Reserve Bank of New York.

4. Empirical results

In this analysis, we estimate Eq. (1) with an AR order 1 and report a 10-week-ahead GFVD in the analysis. Moreover, we estimate the spillover impact among stock market returns at a quantile of 0.5 (i.e., median, $\tau = 0.5$) to measure the mean risk spillovers and estimate the spillover impact at a quantile of 0.05 (i.e. $\tau=0.05$) to examine the tail risk spillovers among stock markets.

Broad picture of mean risk spillovers

Table 2 reports the spillover matrix estimated for the mean (upper panel) and tail risks (lower panel) based on the full sample data. In the matrices, each element is the estimated contribution to the variance decomposition (VD) of group i coming from a shock to group j. For instance, focusing on the mean risk (i.e. upper panel), a shock originated from advanced economies explains 20.8% of the VD of EMEA but only 16.2% of VD of Asia Pacific. In other words, the spillover from advanced economies has a larger impact on EMEA than Asia Pacific.

Fixing the origin of the shock, the last row of Table 2 computes the column average which shows the impact of that shock on other economies. It shows that advanced economies' shock is the largest (19.3%) on average, followed by Asia Pacific (19.2%), Latin America (16.9%), and EMEA (13.8%). This suggests that shocks from advanced economies have the largest spillover effect on others, while the shock from EMEA is relatively modest in general. Fixing the receiver of the shock, the last column of Table 2 computes the row average which summarises the responsiveness of that receiver to shocks generated from others. For example, advanced economies are found to have the largest responsiveness to shocks from the others (20.0%).

[10] Although domestic factors can be an important source of domestic asset volatility, their effect is not controlled for in this analysis because these factors may not be relevant in the context of international financial spillovers.

Spillover impact on Asia Pacific

Focusing on mean risk spillovers to Asia Pacific, the estimated impact is 17.1% on average, in which the spillover within the region is found to be the largest (i.e., 25.6%) while the spillover from EMEA is the smallest (i.e., 12.5%). On tail risk spillovers, the estimated impact increase notably to 24.1% on average, in which the impact is found the largest from Latin America (27.4%) and the smallest from advanced economies (22.9%). This suggests that, the tail risk spillovers are stronger when compared to the mean risk spillovers.

We further check whether the tail risk spillovers have been stronger after the taper tantrum. Figure 2 compares the tail risk spillover impacts on individual Asia Pacific economies in the pre-tapering period with those in post-tapering period. A 45-degree line in each chart is used to identify economies that are more responsive in the pre-tapering period than in the post-tapering period. As can be seen, EMEA and Latin America economies scatter above the 45-degree line, suggesting that spillovers from these economies are substantially larger after the taper tantrum. All advanced economies and most of Asia Pacific scatter slightly below the 45-degree line, suggesting that their spillover impact is weaker in the post-tapering period. That said, the estimated impact remains substantial at around 20%.

Figure 3 compares responsiveness of individual Asia Pacific economies to risk spillovers from other economies in the post-tapering period. As shown in the chart, all the economies are more responsive to tail risk spillovers than to the mean risk spillovers, except for Singapore who has the largest responsiveness to mean risk spillovers. Among these economies, four ASEAN countries (i.e., Thailand, Philippines, Indonesia, and Malaysia) are relatively more responsive to the tail risk spillovers in the region. One possible explanation to their stronger responsiveness to tail risk spillovers is the risk of over-valuations. Figure 4 depicts the scatters of responsiveness against the PE ratio based on samples in the post-tapering period. As can be seen, PE ratios tend to be linearly correlated with responsiveness to the tail risk spillovers but not to the mean risk spillovers. This suggests that an over-valued stock market is likely associated with a stronger response to tail risk spillovers from other markets.

5. Concluding remarks

This paper assesses the spillover impacts on Asia-Pacific stock markets. Using data of 37 stock markets, we find that while the mean risk spillovers to Asia-Pacific stock markets is mainly driven by shocks within the Asia-Pacific region, shocks from regional and non-regional markets are equally considerable in the tail risk spillovers In particular, shocks from Latin America and EMEA have increased notably after the taper tantrum. We also identify that a stronger responsiveness of a stock market to tail risk spillovers from other markets tends to be associated with higher PE ratios.

References

Adrian, T., Crump, R.K., Moench, E., 2013. Pricing the term structure with linear regressions. *Journal of Financial Economics* 110, 110-138.

Aizenman, J., Binici, M., Hutchison, M.M., 2014. The transmission of Federal Reserve tapering news to emerging financial markets. *NBER working paper* No. 19980.

Alter, A., Beyer, A., 2014. The dynamics of spillover effects during the European sovereign debt turmoil. *Journal of Banking and Finance* 42, 134-153.

Apostolakis, G., Papadopoulos, A.P., 2014. Financial stress spillovers in advanced economies. *Journal of International Financial Markets*, Institutions and Money 32, 128-149.

Bernanke, B. S., 2013. Communication and Monetary Policy. Speech at the National Economists Club Annual Dinner, Herbert Stein Memorial Lecture.

Chen, Q., Filardo, A., He, D., Zhu, F. 2016. Financial crisis, US unconventional monetary policy and international spillovers. *Journal of International Money and Finance* 67, 62-81.

Claeys, P., Vasicek, B., 2014 Measuring bilateral spillover and testing contagion on sovereign bond markets in Europe. *Journal of Banking and Finance* 46, 151-165.

Diebold, F. X., Yilmaz, K. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal* 119, 158-171.

Diebold, F. X., Yilmaz, K. 2012. Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers. *International Journal of Forecasting* 28, 57-66.

Fong, T.P.W., Li, K.F., Sze, A.K.W. 2016. Measuring spillovers between the US and emerging markets. *HKMA Research Memorandum* 06.

Forbes (2013) “The “Big C”: Identifying and Mitigating Contagion,” 2012 Jackson Hole Symposium hosted by the Federal Reserve Bank of Kansas City, 23-87.

Forbes, K.J., Warnock, F.E., 2012. Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics* 88, 235-251.

Koenker, R., Bassett, G. 1978. *Regression Quantiles. Econometrica* 46 (1), 33-50.

Li, K.F., Fong, T.P.W., Ho, E.H.C. 2017. Term premium spillovers from the US to international markets. *HKMA Research Memorandum* 05.

Park, C.Y., Mercado,. R.V. 2014. Determinants of financial stress in emerging market economies. *Journal of Banking & Finance* 45, 199-224.

Reboredo, J.C., Rivera-Castro, M.A., Ugolini, A. 2016. Downside and upside risk spillovers between exchange rates and stock prices. *Journal of Banking & Finance* 62, 76-96.

Liow, K.H., 2015. Volatility spillover dynamics and relationship across G7 financial markets. *North American Journal of Economics and Finance* 33, 328-365.

Table 1. Descriptive statistics of stock market return (in log)

Group	Economy	Stock Index	Mean (%)	Median (%)	Max (%)	Min (%)	SD (%)
Asia Pacific	Australia	S&P/ASX 200	-0.02	0.24	9.11	-17.02	2.52
	China	Shanghai Composite Index	-0.01	0.03	13.94	-14.90	3.78
	Hong Kong	Hang Seng Index	0.02	0.26	11.72	-17.82	3.30
	India	S&P BSE SENSEX	0.16	0.29	13.17	-17.38	3.22
	Indonesia	Jakarta Composite Index	0.21	0.42	11.59	-23.30	3.20
	Japan	Nikkei 225	-0.01	0.22	11.45	-27.88	3.38
	Malaysia	FTSE Bursa Malaysia KLCI	0.06	0.16	6.65	-8.48	1.79
	New Zealand	NZX 50 Index	0.12	0.23	5.48	-11.64	1.69
	Philippines	PSE Composite Index	0.19	0.33	11.02	-20.15	2.91
	Singapore	Straits Times Index	-0.02	0.11	15.32	-16.47	2.72
	South Korea	KOSPI	0.07	0.31	17.03	-22.93	2.98
	Taiwan	TAIEX	0.03	0.25	9.41	-11.26	2.76
	Thailand	SET Index	0.17	0.41	10.75	-26.66	2.89
Advanced Europe and America	Canada	S&P/TSX Composite Index	0.02	0.25	12.82	-17.54	2.60
	Denmark	OMX Copenhagen 20	0.16	0.58	11.72	-22.49	3.18
	France	CAC 40	-0.05	0.30	12.43	-25.05	3.31
	Germany	DAX	0.08	0.51	14.94	-24.35	3.36
	Italy	FTSE MIB	-0.19	0.26	10.47	-24.36	3.76
	Norway	OBX Index	0.07	0.37	16.84	-24.78	3.66
	Spain	IBEX 35	-0.11	0.24	11.10	-23.83	3.64
	Sweden	OMX Stockholm 30	0.03	0.33	12.27	-22.53	3.12
	Switzerland	Swiss Market Index	-0.02	0.28	13.16	-25.20	2.80
	UK	FTSE 100 Index	0.01	0.20	12.58	-23.63	2.76
	US	S&P 500 Index	0.09	0.27	11.36	-20.08	2.66
Emerging Europe, the Middle East and Africat	Czech Republic	PX Index	-0.14	0.08	15.57	-30.45	3.36
	Hungary	BUX	0.03	0.10	15.16	-26.89	3.51
	Israel	TA-100 Index	0.05	0.19	10.53	-12.68	2.46
	Poland	WIG	-0.05	0.14	11.58	-17.10	2.80
	Russia	MICEX Index	0.03	0.19	35.42	-27.77	4.47
	Slovakia	Slovak Share Index	-0.06	0.05	12.25	-15.15	2.42
	South Africa	FTSE/JSE Top 40 Index	0.13	0.20	17.92	-11.01	2.90
	Turkey	ISE-100 Index	0.11	0.36	15.76	-19.27	3.86
Latin America	Brazil	Bovespa Index	0.05	0.22	16.84	-22.33	3.76
	Chile	IPSA	0.07	0.14	14.67	-21.60	2.62
	Colombia	IGBC	-0.02	0.22	8.72	-20.50	2.69
	Mexico	IPC	0.10	0.21	18.58	-17.93	2.96
	Peru	S&P/BVL Peru General Index	-0.02	-0.12	19.31	-34.60	4.00

Source: Bloomberg

Table 2. Spillover matrix among four economy groups (full sample period)

Mean risk spillovers	From Adv. Econ.	From Asia Pacific	From EMEA	From Latin America	Row average
To Advanced Econ.	40.0%	11.9%	13.7%	14.4%	20.0%
To Asia Pacific	16.2%	25.6%	12.5%	14.2%	17.1%
To EMEA	20.8%	14.7%	16.6%	12.9%	16.3%
To Latin America	21.0%	17.2%	12.4%	23.5%	18.5%
Column average	19.3%	19.2%	13.8%	16.9%	17.3%
Tail risk spillovers	**From Adv. Econ.**	**From Asia Pacific**	**From EMEA**	**From Latin America**	**Row average**
To Advanced Econ.	23.1%	22.5%	23.5%	28.8%	24.5%
To Asia Pacific	22.9%	23.1%	23.2%	27.4%	24.1%
To EMEA	22.9%	22.7%	23.6%	28.1%	24.3%
To Latin America	23.1%	22.6%	23.4%	27.8%	24.2%
Column average	23.0%	22.7%	23.4%	28.0%	24.3%

Figure 1. Stock market prices in Asia Pacific

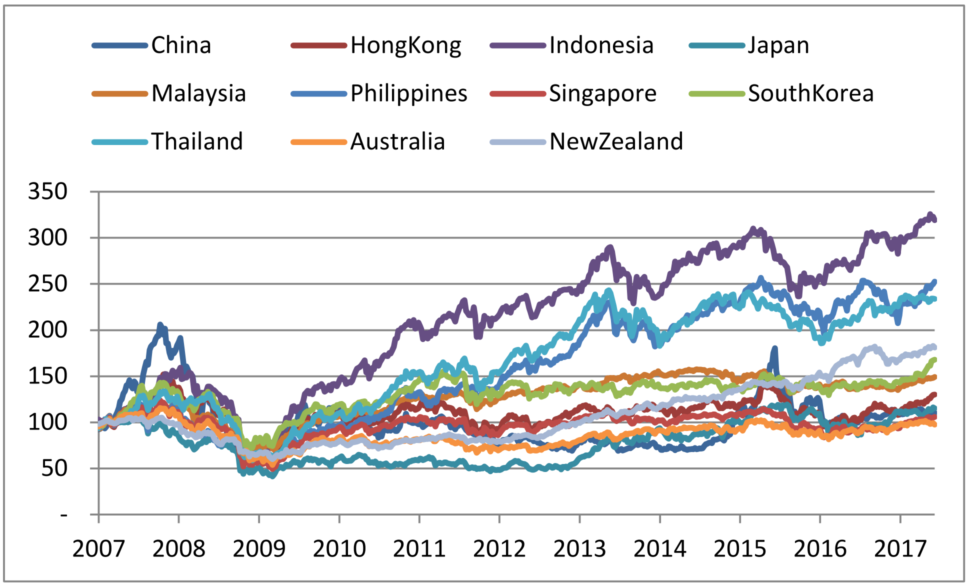
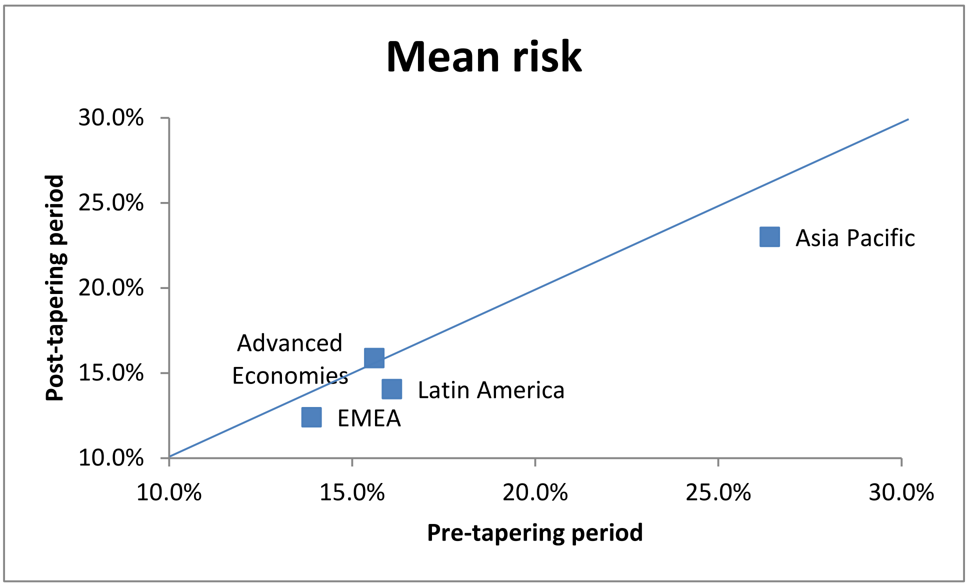


Figure 2. Risk spillovers to Asia Pacific



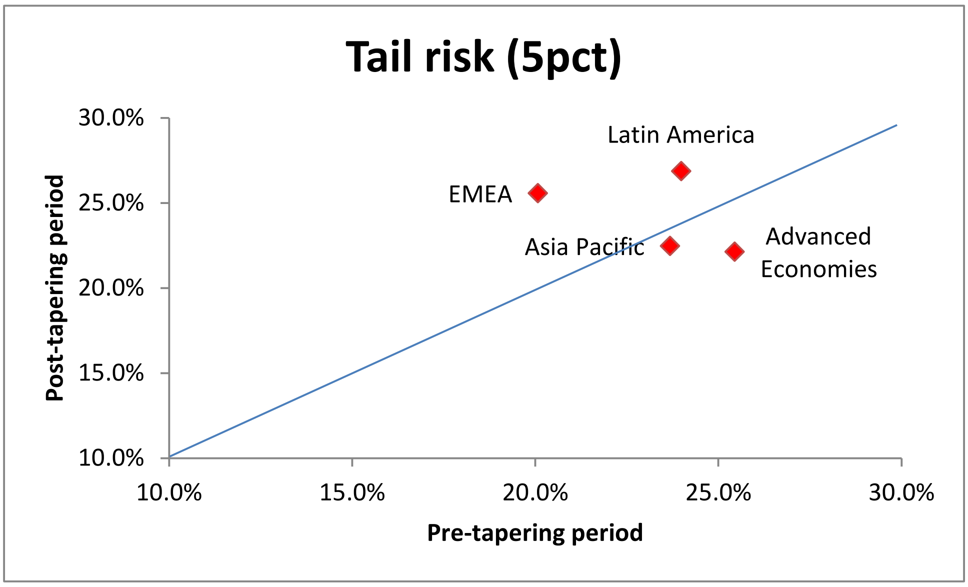


Figure 3. Risk spillovers from Asia Pacific stock markets within the region

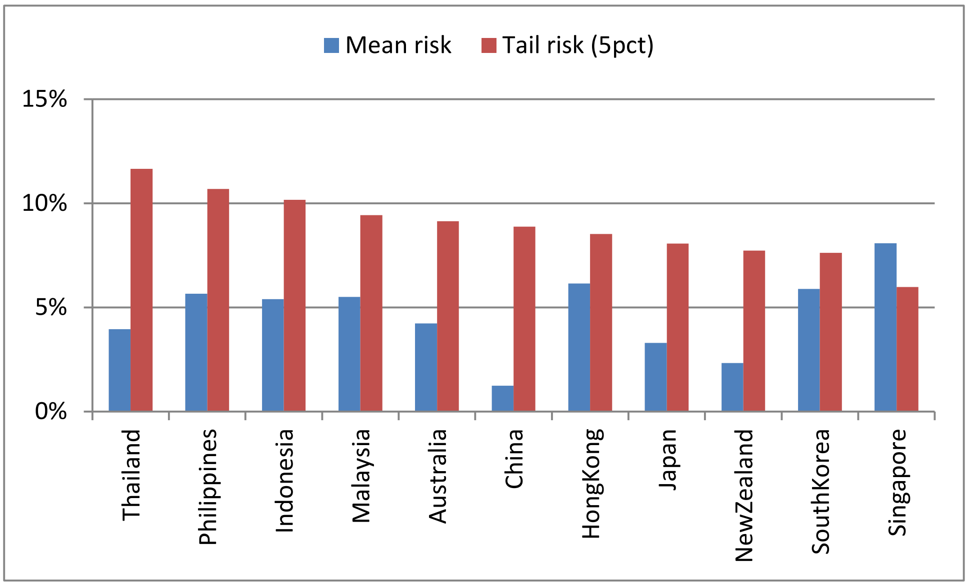


Figure 4. Risk spillovers and price-earning ratios of Asia Pacific economies