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TAIL RISK SPILLOVERS IN ASIA PACIFIC STOCK MARKETS

Key Points:

- *This paper examines financial linkages among Asia Pacific stock markets and those between these markets and other global markets. We evaluate the mean relationship between stock market returns (mean dependence) and relationship between extremely negative returns (tail dependence). The former reflects mostly risks during tranquil periods, while the latter is more likely to be associated with bear markets, periods of crises and financial distress.*

- *Using data on 37 stock markets, we show that mean and tail dependence of stock market prices exhibit a distinct pattern of risk attribution. While Asia Pacific stock markets are mainly affected by shocks originating from the region under mean dependence, shocks from regional and non-regional markets are equally important to Asia Pacific stock markets under tail dependence. In particular, shocks from Latin America and Europe, Middle East and Africa (EMEA) have become more prominent following the taper tantrum in May 2013.*

- *We also find that price-earnings ratios can explain the sensitivity of individual Asia Pacific economies to shocks under tail dependence, but does not seem to offer any explanatory power under mean dependence. This implies that an over-valued stock market could be responsive to spillovers from other markets in times of financial crises, but the response would be inconspicuous in tranquil periods.*

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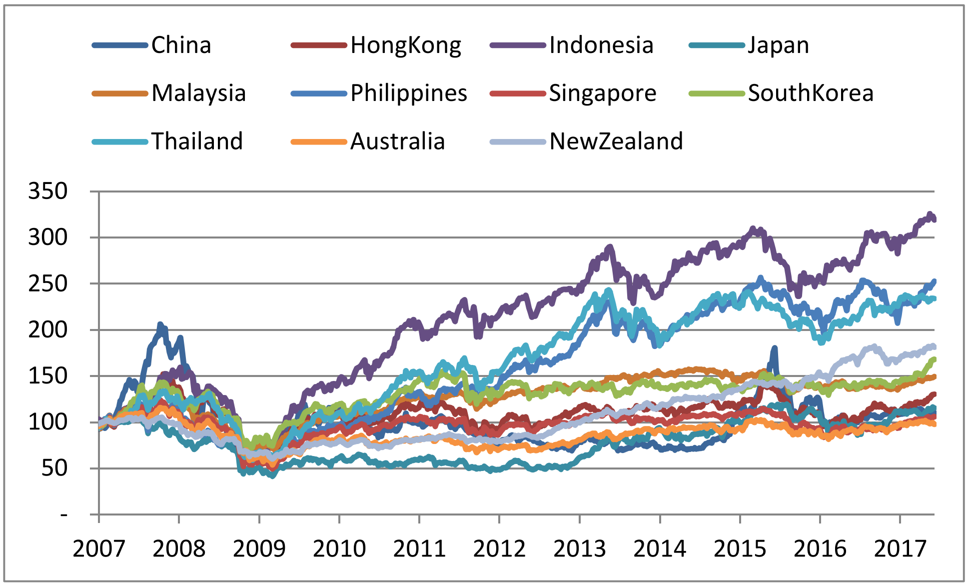
I. INTRODUCTION

Partly due to the spillovers from the quantitative easing program adopted by the US Federal Reserve, stock prices in the Asia Pacific region have risen considerably since 2009 (Figure 1).[1] Within this bull market run, however, there are two notable stock market corrections in 2013 and 2015, with prices in some economies falling by over 20% in a week. With these acute episodes as background, a natural question is "what was the major source of contagion to Asia Pacific stock markets during these sell-offs?" Answers to this question are important for policymakers in seeking 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, affect domestic currency markets and ultimately sovereign creditworthiness.[2]

Figure 1. Stock market prices in Asia Pacific



Source: Bloomberg

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

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[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.

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 risks during tranquil periods which could underestimate the real effects of an international shock in times of financial crises. A more relevant analysis of contagion should evaluate relationships between extremely negative returns, namely tail dependence, which are more likely to be associated with bear markets, periods of crises and financial distress.

In this paper, we examine the financial linkages among Asia Pacific stock markets and those between these stock markets and other global markets. Through estimating these linkages, it is possible to identify major sources of risk spillovers at the mean (namely, mean risk spillovers) and at the tail (namely, tail risk spillovers) within the region. We contribute to the studies of contagion and cross-border spillovers by using multivariate quantile analysis to address the concern in literature about an underestimation of spillover effects on the region.

We show that mean and tail dependence of stock market prices exhibit a distinct pattern of risk attribution. While Asia Pacific stock markets are mainly affected by shocks originating from the Asia Pacific region under mean dependence, shocks from regional and non-regional markets are equally important to the Asia Pacific region under tail dependence. In particular, shocks from Latin America and Europe, Middle East and Africa (EMEA) have become more prominent following the taper tantrum in May 2013. Moreover, price-earnings (PE) ratios, a common indicator for evaluating the risk of overvaluation, can explain the sensitivity of individual Asia Pacific economies to shocks under 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 describe the sample data used in estimation in the next section. The empirical results are presented in section III and we outline the conclusions that can be drawn from this study in the last section. Empirical model in this analysis is discussed in appendix.

II. DATA

We primarily measure stock market spillovers among 13 Asia Pacific economies in this analysis. To make this assessment more comprehensive,

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

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.

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 Africa (EMEA)	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

Weekly returns are used to address the different time-zones problem given that the selected economies are in different continents, and higher frequency data are too noisy and may generate distortion in the estimation.[4] The final sample of 37 stock market returns covers the period from 2 January 2009 to 30 June 2016 and includes a total of 391 observations. Since several studies have identified a structural break during the episode of taper tantrum,[5] we divide the sample into two sub-periods: (1) 2 January 2009 to 24 May 2013 (the pre tapering period) and (2) 27 May 2013 to 30 June 2016 (the post tapering period).

All stock market data are obtained from Bloomberg. The stock indices are transformed into logarithmic returns by taking the first difference of the natural logarithm. Specifically, the return ($R_{i,t}$) for market i in time t is defined as $R_{i,t} = \left[\ln(SI_{i,t}) - \ln(SI_{i,t-1})\right]$ 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;[6] (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;[7] and the US dollar (DXY) index which controls for the effect of the USD appreciation.[8] VIX and DXY are downloaded from Bloomberg and the term premium is sourced from the Federal Reserve Bank of New York.

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4 We use the Friday closing prices in the estimation.

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

6 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.

7 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).

8 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.

III. EMPIRICAL RESULTS

In this analysis, stock returns are considered to potentially depend on its own lags and the lagged returns of other stock markets and the forecasting horizon is set to be 10 weeks.[9] Moreover, the risks measured by mean and tail risk spillovers would occur at a probability of 50% and 5% respectively.[10]

Broad picture of mean risk spillovers

Table 2 reports the spillovers matrix estimated for the mean (upper panel) and tail risks (lower panel) based on the full sample of 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 originating from advanced economies explains 20.8% of the VD of EMEA but only 16.2% of VD of Asia Pacific. In other words, the spillovers from advanced economies have a larger impact on EMEA than the Asia Pacific region.

[9] A 10-week forecasting horizon is chosen because it is commonly used in many empirical studies and empirical results based on a longer horizon remain largely the same.

[10] Specifically, we estimate the spillovers among stock market returns at a quantile of 0.5 (i.e., median, $\tau = 0.5$) to measure mean risk spillovers and estimate the spillovers at a quantile of 0.05 (i.e. τ=0.05) to examine tail risk spillovers. Moreover, we estimate Eq. (1) stated in appendix with an AR order 1 and report a 10-week-ahead GFVD.

Table 2. Spillovers 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%

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 an advanced economies' shock is the largest (19.3%) on average, followed by shocks from Asia Pacific (19.2%), Latin America (16.9%), and EMEA (13.8%). This suggests that shocks from advanced economies have the largest spillover effects, while shocks from EMEA are 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' economy to shocks generated from others. For example, advanced economies are found to have the largest responsiveness to shocks from other economies (20.0%).

<u>Spillover impact on the Asia Pacific region</u>

Focusing on mean risk spillovers to the Asia Pacific region, the estimated impact is 17.1% on average. Spillovers within the region are found to be the largest (i.e., 25.6%) while the spillovers from EMEA are the smallest (i.e., 12.5%). On tail risk spillovers, the estimated impact is higher, at 24.1% on average. The impact of shocks from Latin America (27.4%) have the largest effects, while those from advanced economies have the smallest (22.9%). This suggests that <u>tail risk spillovers are larger than mean risk spillovers</u>.

We further check whether tail risk spillovers have had a larger effect in the post taper tantrum period. Figure 2 compares tail risk spillovers on individual Asia Pacific economies in the pre and 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, <u>EMEA and Latin America economies scatter above the 45-degree line, suggesting that spillovers from these economies are substantially larger after the taper tantrum.</u> All advanced economies and most of Asia Pacific scatter slightly below the 45-degree line, suggesting that their spillovers are smaller in the post-tapering period, but still substantial at around 20%.

Figure 2. Risk spillovers to Asia Pacific

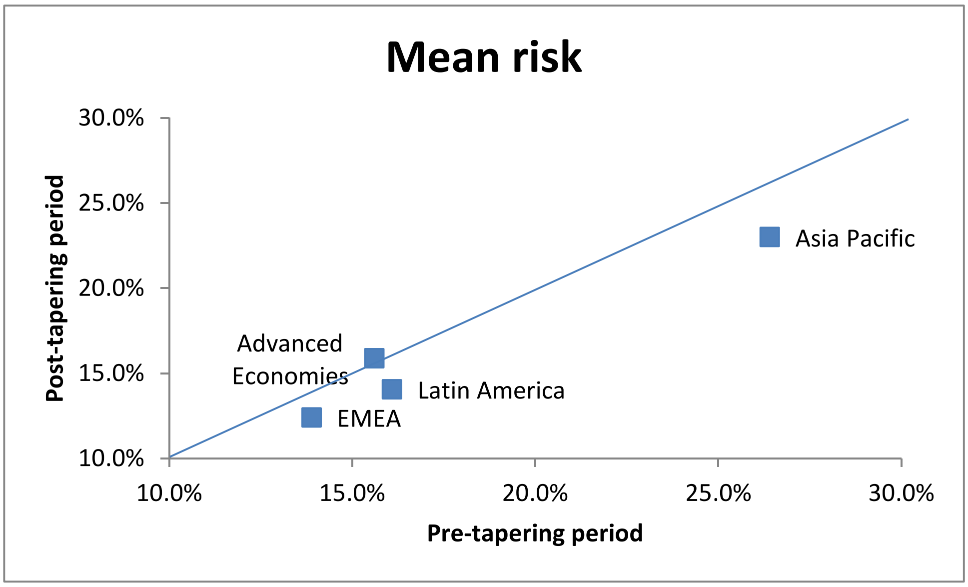


Figure 2 (cont'). Risk spillovers to Asia Pacific

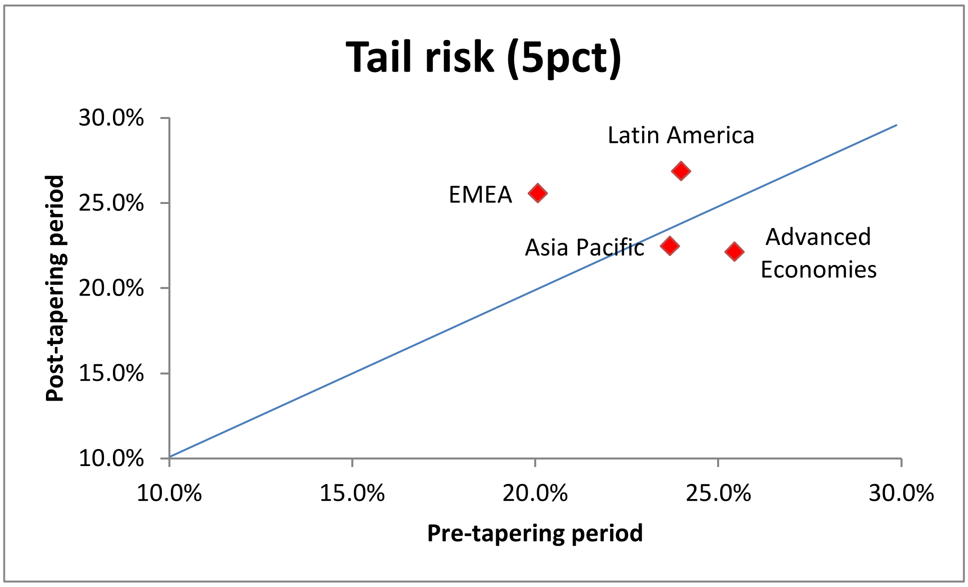
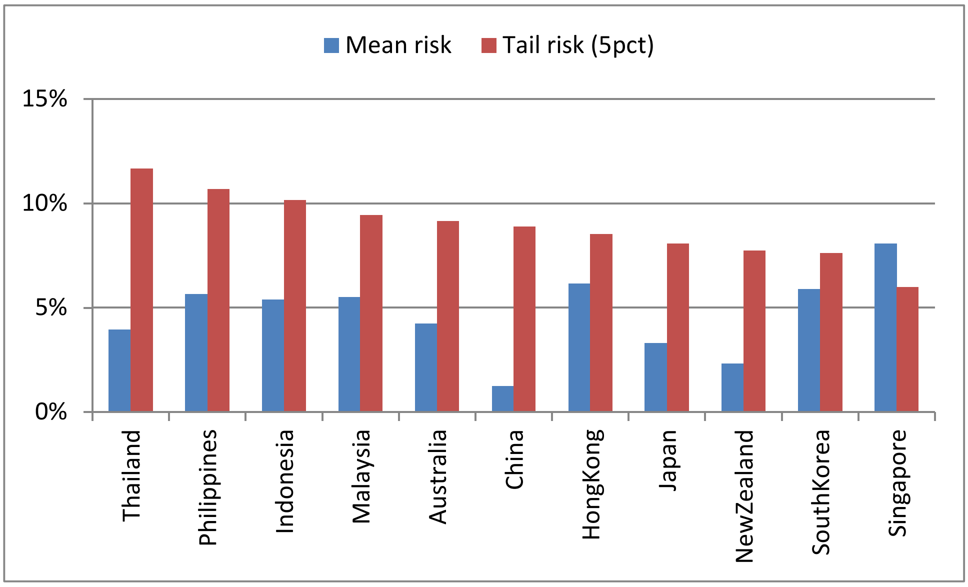


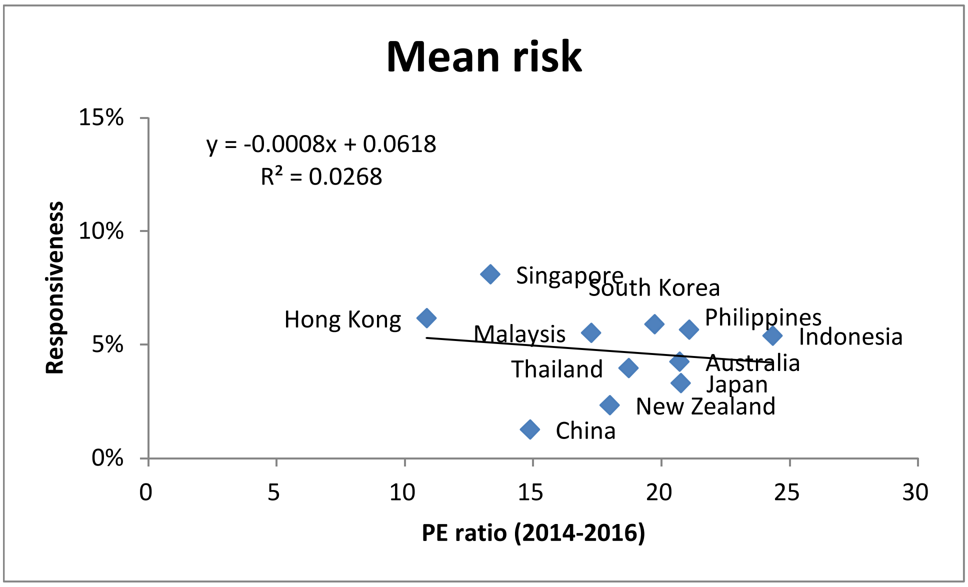
Figure 3 compares the responsiveness of individual Asia Pacific economies to risk spillovers from other economies in the post-tapering period. As shown in the chart, all the economies are more responsive to tail risk spillovers than to mean risk spillovers, except for Singapore which has the largest responsiveness to mean risk spillovers. Among these economies, four ASEAN countries (i.e., Thailand, the Philippines, Indonesia, and Malaysia) are relatively more responsive to tail risk spillovers in the region.

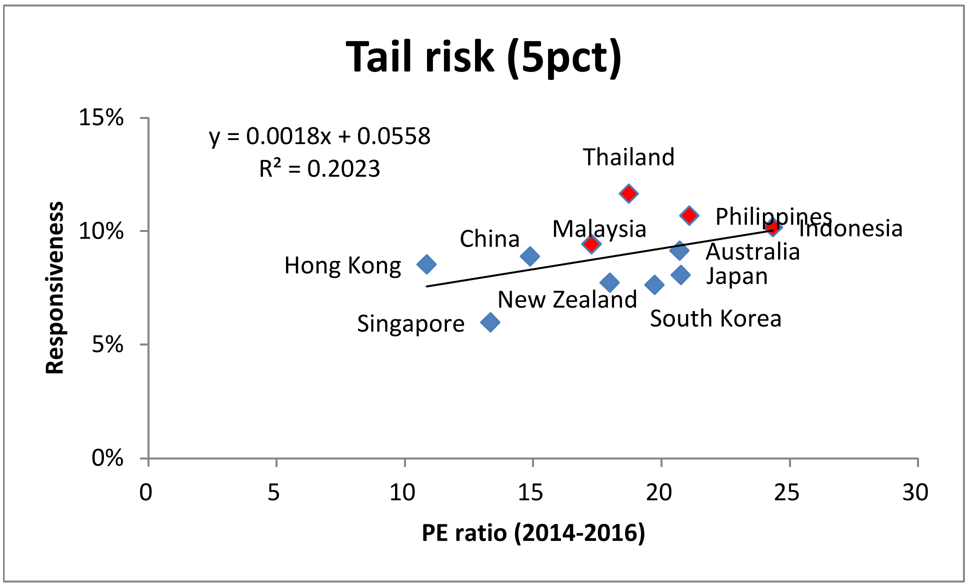
Figure 3. Risk spillovers from Asia Pacific stock markets within the region



One possible explanation to their stronger responsiveness to tail risk spillovers is a greater risk of stock 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, the explanatory powers of a simple linear regression under mean and tail dependence are 2.68% (upper panel) and 20.23% (lower panel) respectively, which suggests that PE ratios tend to be linearly correlated with responsiveness to tail risk spillovers but not to mean risk spillovers. This implies that an over-valued stock market is likely to be associated with a stronger response to tail risk spillovers from other markets.

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





IV. CONCLUDING REMARKS

This paper assesses spillovers from other stock markets to Asia Pacific stock markets. Using data on 37 stock markets, we find that mean risk spillovers to Asia Pacific stock markets are mainly driven by shocks originating from the Asia Pacific region. However, shocks originating from regional and non-regional markets are equally important to Asia Pacific stock markets under tail risk spillovers. We also find that shocks from Latin America and EMEA have increased notably following the taper tantrum. Finally, our results suggest that a stronger responsiveness of one economy's stock market to tail risk spillovers from other markets tends to be associated with higher PE ratios in the domestic stock market.

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Appendix

METHODOLOGY

I. 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 own lags and the lagged returns of other stock markets in the specification.

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

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

where $x_t = (x_{1t}, \dots, x_{Nt})$ is a $N \times 1$ vector of endogenous variables, w_t is a $M \times 1$ vector of exogenous variables, $\Theta_i, i = 1,2, \dots p$ and Φ are $N \times N$ and $N \times M$ coefficient matrices respectively 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:

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

where $\rho_\tau(z) = z(\tau - I(z < 0))$ and $I(*)$ is an indicator function equal to one if the residual is negative and zero otherwise, given a quantile level of τ.[11] In the case of τ equal to 0.5, the resulting forecast of x_t estimates the conditional median of x_t. In the case of τ being very small (large), say 0.05 (0.95), the resulting forecast estimates a sharp decline (rise) in x_t that occurs at a probability of 5%. The estimated coefficients and residuals are used as inputs to the construction of spillover measures discussed in the next sub-section.

[11] More details of quantile regression can be found in Koenker and Bassett (1978).

II. Generalised forecasting variance decomposition

Based on inputs from the previous section, we 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.[12] They explicitly track spillovers of 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.[13]

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

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

where A_i are derived by the recursion $A_i = \Theta_1 A_{i-1} + \cdots + \Theta \; A_{i-}$ 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:

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

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 measure the fractions of the *H*-step-ahead error variances in forecasting x_{it} due to shocks originating from x_{jt}. It is also interpreted as a measure of "spillovers" because it picks up the extent to which shocks originating from x_{jt} are transmitted to x_{it}. When considering $i = j$, the GFVD in Eq. (4) measures "own variance shares" which is the fraction of the *H*-step-ahead error variances in forecasting x_{it} due to shocks originating from itself.

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12 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.

13 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)).

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

$$\tilde{}_{ij}(\ \ ) = \frac{\theta \ \ (H)}{\sum^{N} \ \ \theta \ \ (H)} \tag{5}$$

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

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

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

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