INTERNATIONAL REAL ESTATE REVIEW

Extreme Dependence between Public Real Estate and Stock Markets: Some Asia-Pacific Evidence

Kim Hiang Liow [*]
Department of Real Estate, National University of Singapore, 4 Architecture Drive, Singapore 117566, Email: rstlkh@nus.edu.sg.

Zhuo Lee
Department of Real Estate, National University of Singapore, 4 Architecture Drive, Singapore 117566, Email: xiaomuzi@gmail.com

The main contribution of this study is to examine the extreme dependence between the real estate securities and stock markets in Australia, China, Hong Kong, Japan, Malaysia, the Philippines, Singapore and Taiwan between January 1995 and March 2011. For each market, we derive time series tail dependence coefficients (TDC) which measure how likely financial returns move in extreme market conditions by using the dynamic conditional correlation (DCC) methodology provided by Engle (2002). Overall, our results indicate that Singapore, the Philippines and Hong Kong have the highest extreme real estate–stock market co-movement of at least 50%. In addition, during the global financial crisis (GFC) period, the securitized real estate and common stock markets in China, Hong Kong, Japan, the Philippines and Singapore displayed the highest extreme dependence to react together to financial turmoil. The results in this paper also show that the extreme dependence patterns of real estate-stock markets are similar for many of the Asia-Pacific economies. Finally, correlation coefficients are not adequate for explaining extreme co-movements between the securitized real estate and common stock markets in the longer period, as well as in the two-year GFC periods. Our TDC modeling with Asia-Pacific securitized real estate and stock markets provide useful information and advice to international investors and risk management personnel in tactical asset allocation so as to manage the extreme dependence between securitized real estate and common stock markets.

---

[*] Corresponding author

Keywords

Extreme dependence; Tail dependence coefficient; Dynamic conditional correlation; Correlation coefficient; Securitized real estate markets; Stock markets

1.   Introduction

In this paper, we are concerned with public real estate which comprises listed property companies, listed real estate operating companies (REOCs) and listed real estate investment trusts (REITs). For these investment vehicles, their underlying assets (i.e. real estate) in which they invest are transacted in the private real estate markets; however, their shares are traded in the stock markets. Consequently, it is expected that public real estate markets would have a higher volatility than the direct real estate market which is in line with the broader stock market. A strong linkage between local real estate markets and stock markets – for small locally oriented stock markets in particular – could also be driven by the fact that most real estate companies are invested domestically only and thus are much more vulnerable to domestic economic shocks. Due to the strong growth in the global securitized real estate markets over the past decade (RREEF, 2007), public real estate (which represents partial and indirect ownership interest in the underlying real estate assets) has been considered as an essential asset class that deserves some allocation in mixed-asset portfolios and is often considered as a suitable portfolio diversifier (Idzorek et al. 2006).

The interactions between public real estate and stock have received much attention in the literature. For example, Clayton and MacKinnon (2003) report that securitized real estate is closely linked to the stock market. However, less formal attention has been given to the relationships between securitized real estate and stock markets under extreme conditions, e.g. the market turmoil periods associated with the 1997 Asian Financial Crisis (AFC) and the recent global financial crisis (GFC) events. Separately, the limits of using linear correlation coefficients to model the relationship between two random time series have also been extensively reported in the literature. Moreover, with increasing emphasis on risk management due to financial turmoil, such as the AFC and GFC events, it is necessary to understand the impact of adverse movements in one market on other markets by using alternative measures since extreme dependence cannot be explained by ordinary correlation coefficients.

The main contribution of this study is to assess the extreme dependence between the real estate securities and stock markets in Australia, China, Hong Kong, Japan, Malaysia, the Philippines, Singapore and Taiwan between January 1995 and March 2011. Following So and Tse (2009), for each pair of

real estate and stock markets,   we derive the tail dependence coefficient (TDC) as a measure of extreme co-movements in returns, which is a conditional likelihood that extreme market losses occur at the same time. Intuitively, tail dependence refers to the strength of a relationship among the tails of return distribution. Hence, the TDC measure is particularly appropriate for measuring the degree of cross-market or cross-asset linkages (e.g. in a domestic economy) during crisis times. To our knowledge, this is probably the first real estate study that utilizes the TDC methodology to measure how securitized real estate returns move with stock market returns in extreme market conditions.

With the use of the daily returns of indices from the Standard and Poor (S&P) Global Property Index between January 1995 to December 2011, which gives us at least a 16-year horizon, and covers major recent market events in Asia, like the AFC, the IT bubble, SARS and the recent 2007 GFC, the three objectives of this study are:

(a) to examine the extreme dependence structure of eight Asia-Pacific securitized real estate-stock markets by estimating the TDC for each pair of markets. The TDC is a measure of the likelihood that returns move together in extreme market conditions. We will appeal to the dynamic conditional correlation (DCC) model provided by Engle (2002) and a rolling window approach to derive the time series of TDC for this purpose, and

(b) to analyze the relationship between the time series structures of TDC and the correlation coefficient to evaluate how extreme dependence influences linear dependence and vice versa. Specifically, we study the cross-correlation between the two series to understand any lead-lag behavior between them, with particular attention given to the AFC and GFC periods, where appropriate.

The organization of this paper is as follows. Section 2 provides a brief literature update. This is followed by Sections 3 and 4 which, respectively, describes the data sample and explains how TDC can be dynamically modeled by using the multivariate DCC-GARCH model. Section 5 presents the empirical results. The evolution of TDC patterns between the securitized real estate and common stock markets is given focus, and the relationships between TDC and correlation coefficients are evaluated. Finally, some concluding remarks are presented in Section 6.

2.   Literature Review

A review of prior literature has indicated that although correlation is a popular measure of market dependence, securitized real estate returns (similar to stock market returns) are heavy-tailed. Consequently, correlation might give

investors a misleading description of dependence. This is because statistically, the Pearson correlation ρ is the average of deviations from the mean. As such, it makes no distinction between large and small realizations, and does not distinguish between positive and negative returns. In addition, it assumes a linear relationship and a multivariate Gaussian distribution, which might lead to a significant estimation of the risk from joint extreme events (Poon et al. 2004)

During crisis times when the emphasis is to minimize extreme market losses, market dependence structures should be examined from an extreme dependence perspective. As pointed out by Embrechts et al. (2002), dependencies between extreme events such as the July 1997 AFC and the recent late 2007 US subprime mortgage crisis require alternative dependence measures to support risk management and asset allocation strategies. In this context, the concept of tail dependence is appropriate to describe the dependence between extremal data in finance. Intuitively, tail dependence describes the cross-market or cross-asset relationships during crisis times, which are different from relationships during normal times. One good example is where two asset returns display greater co-movements during market downturns than during market upturns. Mathematically, according to Frahm et al. (2005), *(X, Y)* is upper tail dependent if $\lambda_U > 0$ and upper tail independent if $\lambda_U = 0$. The lower tail dependence coefficient is defined as $\lambda_L = \lim_{t \to 0} P\{G(X) \leq t \,/\, H(Y) \leq t\}$. Furthermore, if *(X, Y)* is bivariate t-distributed, then $\bar{t}_{\alpha+1}$ is the survival function of a univariate Student's t-distribution with $\nu + 1$ degrees of freedom, the time series of time dependence coefficient (TDC) of any *(i, j)* pair can be computed by using the equation below (McNeil et al. 2005):

$$\lambda(\text{TDC}) = 2\bar{t}_{\alpha+1}\left(\sqrt{\alpha + 1}\sqrt{1 - \rho/1 + \rho}\right).[1]$$

---

[1] There are a few technical issues which a reviewer has raised; we wish to briefly clarify: (a) λ_U and λ_L are called coefficients of tail dependence. They measure the probability of observing an extreme value of one variable given that the other variable has an extreme value. *(X, Y)* is lower tail dependent if $\lambda_L > 0$ and upper tail independent if $\lambda_L = 0$. (b) As one variable reaches its upper limit, the change of the other variable is being close to its upper limit and only approaches zero for asymptotically independent random variables; but to a non-zero limit for asymptotically dependent variables. Consequently, the extreme values in each variable can simultaneously occur only for asymptotically dependent variables, but will always exist at separate times for asymptotically independent variables. (c) The non-normality in asset return joint distribution, that is, a fall in values of assets beyond some threshold which can trigger a fall in values of other assets that are initially weakly correlated, has been popularly documented in the literature. In addition, the multivariate t-distribution is a common alternative for analyzing elliptical models. (d) Our additional tests (detailed results not reported) show that the bivariate normality assumption was unequivocally rejected by the data; however, the bivariate skewness test and many of the univariate skewness tests could not reject a t-distribution with ν=10, 8 or 6, a conclusion similar to what we obtained by using the kurtosis test.

In contrast to the considerable amount of literature on the analysis of extreme risks and tail dependence for the stock market (see for example, Poon et al. 2004; So and Tse 2009), less formal attention has been received in the real estate literature with only five notable exceptions. While Liow (2008) examines how the Asian AFC has influenced the value-at-risk (VaR) dynamics in several international securitized real estate markets, Lu et al. (2009) employ five methods to estimate the VaR for REIT portfolios. Zhou and Anderson (2010) conduct an extreme risk study on nine major international REIT markets. They also find that the extreme risks for REITs are generally higher than those of stock markets, especially during the recent GFC. Finally, Zhou and Gao (2010) use the flexible symmetrized Joe-Clayton (SJC) copula to estimate the tail dependence for six major real estate security markets. They find that the six markets display different strengths and dynamics of tail dependence. They also demonstrate that the widely used Pearson linear correlation coefficient is an inadequate measure of market linkages, especially during a crisis time. More recently, Hoesli and Reka (2011) assess market contagion by testing for structural changes in tail dependencies modeled by using the SJC copula. They document different dynamics between the conditional tail dependences and correlations between local and global securitized real estate markets, as well as between securitized real estate markets and common stock markets in the US, the UK and Australia.

3.   Data

We focus on eight pairs of Asia-Pacific securitized real estate and common stock markets from January 1995 to March 2011, the longest period for which all 16 time series return series are available. These eight real estate security markets are in Australia, China, Hong Kong, Japan, Malaysia, the Philippines, Singapore and Taiwan. They are in different stages of development and have different market capitalizations, institutional and regulatory frameworks, market transparency levels, trading systems and transaction costs. For example, with strong economic growth and improved real estate market maturity and transparency levels in recent years, securitized real estate investments have been seen to play an increasingly important role in the Greater China economies and stock markets

The available real estate and stock market data are daily returns of indices in the Standard and Poor (S&P) Global Property Index and BMI database. Tables 1 and 2 provide the usual descriptive statistics of the local valued returns for all daily real estate and continuous return series, respectively. Over the full study period, the highest and the lowest average mean real estate daily returns are recorded by China and Taiwan at 0.0259% and -0.0208%, respectively. Except for Japan, all seven other stock market returns have outperformed the respective securitized real estate market returns. The range of stock market return is between -0.0123% (Japan) and 0.0319% (China). The historical

standard derivations or volatilities range between 1.16% for Australia to 2.53% for China. Comparatively, all stock markets are less volatile with daily standard deviation ranges between 1.01% (Australia) and 2.48% (China) Six real estate security markets have positive skewnesses, which indicate asymmetry towards positive returns, whereas six stock markets have negatively skewed returns. Within the two asset classes, the kurtosis appears to be the largest for Malaysia real estate (25.77) and China stock (265.41), which indicate high tail risk in all securitized real estate and stock markets which may be ignored by investors. Finally, the Jarque-Bara (JB) statistics indicate that all securitized real estate and stock market daily return series are highly non-normal. It is thus important to explore possible extreme dependences among the real estate security markets that may be triggered by their co-movements or common tail risk in response to adverse market events.

Table 1   Summary Statistics of Securitized Real Estate Daily Returns in Local Currency (1995.3-2011.3)

	Mean （%）	Maximum （%）	Minimum （%）	Std. Dev. （%）	Skew ness	Kurt osis	Jarque- Bera
Australia	-0.0009	7.13	-10.74	1.16	-0.92	15.46	27945.34
China	0.0259	13.58	-12.66	2.53	0.00	6.34	1965.65
Hong Kong	0.0172	21.49	-14.42	1.91	0.33	12.58	16230.20
Japan	-0.0026	14.07	-12.02	2.02	0.18	7.01	2857.96
Malaysia	-0.0161	22.94	-21.79	1.84	0.90	25.77	91810.54
Philippines	0.0026	26.08	-12.28	2.16	0.82	14.71	24626.34
Singapore	0.0002	25.79	-13.80	1.97	0.96	16.38	32158.18
Taiwan	-0.0208	12.37	-25.38	2.18	-0.23	8.49	5350.28

Source: S & P Global Property Index.

Table 2   Summary Statistics of Stock Market Daily Returns of 8 Asian Countries (1995.3-2011.3)

	Mean （%）	Maximum （%）	Minimum （%）	Std. Dev. (%)	Skew ness	Kurtosi s	Jarque-Bera
Australia	0.0284	10.48	-10.45	1.01	-0.48	14.51	23496.47
China	0.0319	66.40	-68.75	2.48	-0.41	265.64	12143826.00
Hong Kong	0.0297	16.83	-18.50	1.59	-0.23	19.07	45518.12
Japan	-0.0123	17.14	-15.22	1.42	-0.10	16.14	30414.25
Malaysia	0.0305	20.39	-21.81	1.59	1.16	40.88	253521.90
Philippines	0.0244	19.34	-19.38	1.57	0.21	20.99	57011.15
Singapore	0.0131	42.65	-44.02	1.73	-0.02	192.24	6304065.00
Taiwan	0.0048	22.56	-27.34	1.69	-0.53	27.87	109096.30

Source: S & P Global BMI.

4.   Methodology

4.1   Modeling the Dynamic TDC Structure

Our TDC modeling is based on the DCC-GARCH methodology provided by Engle (2002).[2] The conditional covariance terms are assumed to follow the DCC (1, 1) specification:

$$h_{ij,t} = \rho_{ij,t}\sqrt{h_{ii,t}}\sqrt{h_{jj,t}} \tag{1}$$

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} \tag{2}$$

$$q_{jj,t} = (1 - theta1 - theta2)\bar{\rho}_{ij} + theta1 * \eta_{i,t-1}\eta_{j,t-1} + theta2 * q_{jj,t-1} \tag{3}$$

where $q_{jj,t}$ is the conditional covariance between the standardized residuals, and $\bar{\rho}_{ij}$ is the unconditional correlation between residuals $\varepsilon_{i,t}$. Equation (3) is the DCC model in which a and b are scalar parameters to capture the effects of previous (first lagged realization) standardized shocks and dynamic conditional correlations on current dynamic conditional correlations, respectively.   The $q_{jj,t}$ expression will be mean-reverting when $a + b < 1$. This specification reduces the number of parameters to be estimated and makes the estimation of time-varying correlation more tractable.

Finally, Engle (2002) shows that the log-likelihood of the estimators may be written as:

$$L(\theta) = -\frac{1}{2}\Sigma_{t=1}^{T}\left[\left(n\,log(2\pi) + 2\,log|D_t| + \varepsilon'D_t^{-1}D_t^{-1}\epsilon\right) + \left(log|V_t| + \eta_t'V_t^{-1}\eta_t - \eta_t'\eta_t\right)\right] \tag{4}$$

where n is the number of equations; T is the number of observations; θ is the vector of parameters to be estimated; D_t is the diagonal matrix of time varying standard deviations obtained from Equation (4) and V_t is the time varying correlation matrix.

With the time-varying correlation matrix, the time series of TDC of any *(i, j)* pairs are:

$$\lambda_{ij,t} = 2\,\bar{t}_{v+1}\left(\sqrt{\frac{(v+1)(1-\rho_{ij,t})}{(1+\rho_{ij,t})}}\right) \tag{5}$$

---

[2] The TDC framework of So and Tse (2009) is based on the time-varying MGARCH model proposed by Tse and Tsui (2002). See Liow et al. (2009) for using the DCC model to study correlations in international securitized real estate markets. Two other technical issues that we wish to clarify: (a) we have used a bivariate DCC-GARCH model to analyze a pair of real estate securities and stock markets in each economy. It may also be possible to include all 8 countries (16 asset markets) in a multivariate model. As our focus is on real estate-stock market tail linkage within each country, we believe the bivariate specification is sufficient for our purpose. (b) Capturing the existence of asymmetric correlation in our dataset was not our main concern, as such, we did not add in an asymmetric specification to the DCC-GJR-GARCH model.

where $\bar{t}_{v+1}()$ is the survival function of a univariate Student's t-distribution with $v + 1$ degrees of freedom (McNeil et al. 2005). Equation (5) implies that TDC is a transformation of normal correlations (So and Tse 2009).

In addition, to capture structural changes in the conditional distribution of the return vector, the parameter estimates are updated every week. In other words, a rolling-sample procedure is adopted whereby the estimation window is fixed at one year (about 250 daily returns) while updating the information for parameter estimation every week (5 days). By adopting this rolling procedure, we hope to capture any adverse movement in the market that might cause potential structural changes in the model parameters Finally, a rolling sample one-step (week) forecast of the TDC between a real estate – stock market pair is generated.

4.2   Relationship between TDC and Correlation Coefficient (ρ)

TDC captures the tail behavior of a joint return distribution while ρ measures the linear association between two return variables. With the times series of TDC and ρ derived from the DCC model, we proceed to compare their magnitudes, as well as analyze the relationship between the two measures by studying the lead-lag behavior between the two series and thereby assess how extreme dependence influences linear dependence and vice versa. We use a cross-correlation function (CCF) for this analysis. Specifically, if CCF (k) is significant for a negative k, we can say that ρ leads TDC since we can infer the future TDC value given the current value of ρ. On the other hand, TDC leads ρ if CCF (k) is statistically significant for a positive k. We will focus our analysis with reference to the AFC and GFC events.

5.   Empirical Results

Table 3 presents the average rolling estimate for our AR (1)-GJR-GARCH (1, 1) – DCC model over the full sample period. The result indicates that the persistence of volatility represented by $\alpha + \beta$ is reasonably high, which ranges from 0.7062 for Chinese stock to 0.9541 for Chinese real estate. For the correlation process parameter, the average a + b is 0.7877. The average degree of freedom is 10.5870, which implies a reasonably significant fat-tailed structure in the joint distribution of returns. Figure 1 shows a plot of the two moving DCC parameters and the degree of freedom from fitting the securitized real estate and stock returns. It can be observed that the time series plots of the estimated parameters display great fluctuations over the full period. As such, our rolling-sample procedure is able to capture the model parameter changes over the entire time horizon.

Table 3
Average value of MGARCH parameters between real estate and stock market returns

AR process of correlation matrix					Univariate GARCH					
a	B	v			Mean value x 10^ (-4)	ar(1)	Variance value x 10^4	α（ARCH）	β（GARCH）	Γ（GJR）
0.0496	0.7381	10.5870	Australia	Real Estate	2.3461	0.0113	4.0994	0.1208	0.8220	2.3351
				Stock	33.8202	-0.0085	3.1199	-0.0436	0.8620	0.1984
			China	Real Estate	1.4889	0.0769	0.6854	0.0920	0.7584	0.0584
				Stock	7.0920	0.1177	1.6115	-0.0491	0.7553	1.0558
			Hong Kong	Real Estate	5.4665	0.1156	1.3178	0.0682	0.8859	0.1015
				Stock	30.4738	0.0755	2.9841	0.0715	0.8345	0.1542
			Japan	Real Estate	-0.0003	0.1393	0.6440	0.0556	0.8157	0.0855
				Stock	18.2228	0.0890	1.8557	0.0081	0.7946	0.1852
			Malaysia	Real Estate	6.5073	0.0996	4.7992	0.1949	0.7303	0.0380
				Stock	1.5180	0.2044	3.1957	0.1563	0.7016	2.3008
			Philippines	Real Estate	0.8938	0.0762	0.3980	0.0215	0.8140	0.0821
				Stock	0.0147	0.1919	0.5225	0.0921	0.7875	0.0856
			Singapore	Real Estate	1.6961	0.0495	1.5699	0.0620	0.7945	0.0537
				Stock	8.3136	0.0841	3.6992	0.0289	0.7882	2.0079
			Taiwan	Real Estate	0.0001	0.0607	0.3486	0.0972	0.8160	0.0357
				Stock	26.9480	0.0292	1.0202	0.1604	0.7604	0.1422

Notes: v represents the average value of degree of freedom estimated from rolling model.

Figure 1   Time Series Plot of the Estimated DCC-MGARCH Parameters
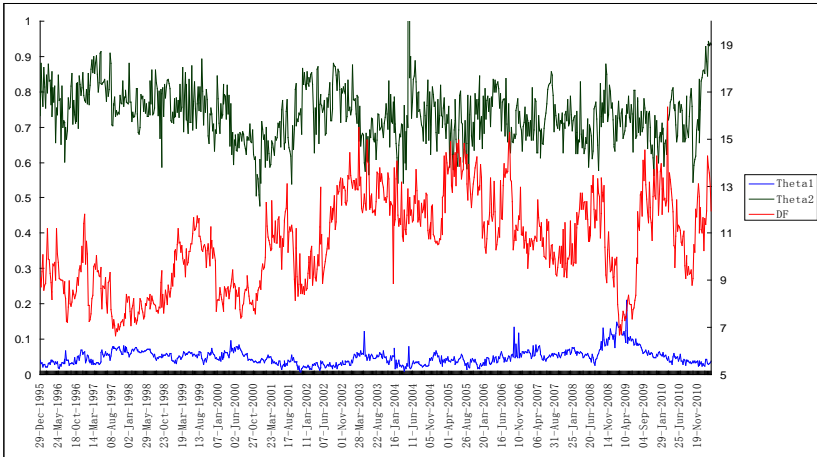
Note: The y-axis on the left corresponds to the values of the DCC parameters (theta1 and theta2) and that on the right corresponds to the value of degrees of freedom

Table 4 present the summary statistics of the average TDCs from January 1995 to March 2011 for eight pairs of securitized real estate and stock markets. The highest TDC is from the Singapore pair (0.5526), and followed by the Philippines (0.5452) and Hong Kong (0.5233), whereas the lowest TDC is from the China pair (0.3853). Consequently, on average, if the Singapore stock (real estate) returns have an extreme movement to a very low level, the chance that its real estate (stock) returns will have an extreme movement on the same week is at least 55%. This result is consistent with the understanding that real estate is an important asset component of the Singapore stock market. Furthermore, many of the real estate companies are investing locally. Consequently, it is expected that the two asset markets are vulnerable to domestic economic shocks and volatility spillovers, from the stock market to the real estate market (or vice-versa). This was the case, e.g. during the AFC, in which the market prices of real estate securities sharply declined and then affected other sectors of the stock market, such as the financial sector. Similarly, the real estate security market is a very important component of the Hong Kong stock market. As such, the high TDC of the Hong Kong pair (0.5233) is not unexpected.

Further analysis observes that the TDCs of China, Hong Kong, Japan, the Philippines and Singapore reach their local historical high around the time of the GFC (between March and November 2008). The respective peaks are

Singapore (0.7227, March 2008), Philippines (0.6658, July 2008), Hong Kong (0.7627, June 2008), China (0.6700, June 2008) and Japan (0.6731, November 2008). In addition, Taiwan and Australia reach their respective TDC peaks around April 2009 and March 2011 (post GFC period), respectively. This observation can be explained in that during the GFC period, the respective securitized real estate and common stock markets show the highest extreme dependence, which indicate that their real estate and stock markets move closely in the same direction to react together to financial turmoil. Our explanation is further supported by Table 5 which provides the average TDC values for six different sub-periods (1995-1996, 1997-1998, 1999-2001, 2002-2006, 2007-2008 and 2009-2001). While the highest average TDC is reported for Australia (0.5096) and the Philippines (0.6043) during the 1997-1998 (AFC) period, the highest average extreme dependence of Japan (0.5745), China (0.6003), Hong Kong (0.6999) and Singapore (0.6561) happens between 2007 and early 2009 period.

Table 4   Descriptive Analysis of TDCs between Securitized Real Estate Markets and Stock Market Returns from January 1995 to March 2011

	Mean	Median	Maximum	Minimum	Std. Dev.
Australia	0.4220	0.4380	0.7697	0.2290	0.0823
China	0.3853	0.3300	0.6700	0.1201	0.1567
Hong Kong	0.5233	0.4867	0.7627	0.2547	0.1338
Japan	0.5141	0.5361	0.6731	0.2731	0.0886
Malaysia	0.4633	0.4354	0.6762	0.3222	0.0928
Philippines	0.5452	0.5480	0.6658	0.3934	0.0664
Singapore	0.5526	0.5631	0.7227	0.3633	0.0847
Taiwan	0.4073	0.4004	0.6262	0.2513	0.0647

Table 5   Average TDCs between Securitized Real Estate and Common Stock Markets in Different Sub-periods

	1995-1996	1997-1998	1999-2001	2002-2006	2007-2008	2009-2011
Australia	0.4885	**0.5096**	0.3689	0.3581	0.4951	0.4634
China	0.1510	0.2480	0.2703	0.3783	0.5955	**0.6003**
Hong Kong	0.2940	0.4050	0.4291	0.5281	0.6930	**0.6999**
Japan	0.5255	0.5184	0.4120	0.5249	**0.5745**	0.5650
Malaysia	**0.6411**	0.5911	0.5055	0.3805	0.4287	0.4268
Philippines	0.5363	**0.6043**	0.6044	0.4882	0.5768	0.5160
Singapore	0.5779	0.5859	0.5255	0.4753	0.6272	**0.6561**
Taiwan	**0.5100**	0.4609	0.3750	0.3657	0.3812	0.4776

*Note:* Figures in bold are the highest for the respective markets from the six sub-periods

The time series plot of TDCs for the eight real estate-stock market pairs are shown in Figure 2. In addition, Table 6 lists the co-movements of the TDCs between different market-pairs. Some pertinent observations are documented. The TDC profile of China is very similar to that of Hong Kong (the cross-TDC correlation coefficient is 0.989) in that both TDCs are trending upward until the GFC period. One implication is that for these two economies, the securitized real estate market is increasingly integrated with the common stock market in that the dependence with great financial uncertainty becomes stronger in the two Greater China economies. Other similar cross-TDC patterns include Singapore and Australia (correlation coefficient is 0.652), and Japan and Australia (correlation coefficient is 0.529). In contrast, the TDCs of Malaysia and Philippines are negatively correlated with China, Hong Kong and Japan; in particular, the TDC of Malaysia has a high negative correlation with China (-0.566) and Hong Kong (-0.592). This is explained by the declining of the Malaysia's TDC pattern until 2006, followed by some intermittent upward trends thereafter. Overall, there are 20 positive and eight negative cross-TDC correlation coefficients, which indicate that for the majority of the Asian economies, the extreme dependence patterns between the securitized real estate and common stock markets are similar. Turning our attention now to the 2007-2008 (GFC) period, we observe in addition to the strong co-movement between the TDCs of Malaysia and the Philippines, as well as between that of China and Hong Kong, the TDC pattern of Singapore is similar to that of China (correlation coefficient is 0.747) and Hong Kong (correlation coefficient is 0.773), Within the Greater China group, there are also strong co-movements between the TDCs of Taiwan and Hong Kong (correlation coefficient is 0.657), as well as between Taiwan and China (correlation coefficient is 0.520). Overall, there are 21 pairs that have similar TDC co-movements with stronger TDC magnitudes reported in several cases. Our results thus provide support to the argument that real estate markets are becoming more integrated with the local stock markets in periods of financial turmoil in most of the Asia-Pacific economies. Further extension of this work includes the examining of the driving forces behind the correlations; e.g. by modeling potential economic determinants of the TDC structure (see for example: Yang, Zhou and Leung, forthcoming). This is because a better understanding of the dynamic changes in a TDC structure, in addition to the normal correlation structure, is critical in understanding the risk-return performance of international public real estate and stock markets, as well as the nature and extent of real estate and stock market integration.

Table 6   Co-movement of TDCs between Different Market Pairs

	Australia	China	HK	Japan	Malaysia	Philippines	Singapore	Taiwan
Australia	1	**0.176**	**0.143**	**0.529**	**0.437**	**0.389**	**0.652**	**0.480**
China	-0.191	1	**0.989**	**0.367**	**-0.566**	**-0.257**	**0.362**	**0.034**
Hong Kong	0.213	0.803	1	**0.336**	**-0.592**	**-0.242**	**0.299**	**-0.019**
Japan	-0.697	0.709	0.250	1	**-0.225**	**-0.187**	**0.463**	**0.289**
Malaysia	0.752	-0.152	0.377	-0.663	1	**0.529**	**0.274**	**0.429**
Philippines	0.756	-0.332	0.189	-0.790	0.858	1	**0.294**	**-0.037**
Singapore	0.344	0.747	0.773	0.234	0.348	0.141	1	**0.486**
Taiwan	-0.067	0.520	0.657	0.300	0.108	-0.037	0.354	1

Note: This table presents the correlation (co-movement) of TDCs for the 9 regions. Bolded numbers (above the diagonal) are the correlation coefficients between the TDCs for 1995-2011 (full period). Numbers below the diagonal are the respective correlation coefficients for the 2007-2008 GFC period.

Figure 2   Time Series Plots of TDCs between Securitized Real Estate and Common Stock Markets: Jan 1995 – Mar 2011
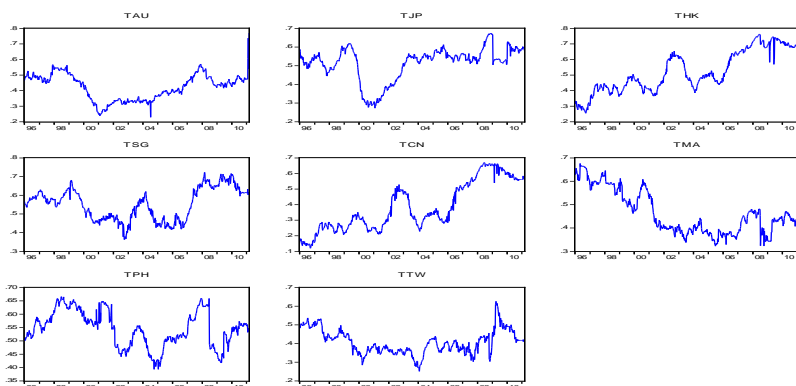
Legend: TAU (TDC of Australia); TJP (TDC of Japan), THK (TDC of Hong Kong), TSG (TDC of Singapore); TCN (TDC of China); TMA (TDC of Malaysia); TPH (TDC of the Philippines); and TPW (TDC of Taiwan).

Finally, Table 7 provides consideration of the relationship between TDCs and correlation coefficients. The pre-whitened TDC and correlation coefficient are the residuals obtained by fitting an appropriate AR model to the logarithm of the TDC and correlation coefficient. For the full period, the numbers indicate that the cross-correlation is all positive at lag 0, with the highest values reported for China (0.4589) and Hong Kong (0.2334), which imply moderate contemporaneous association between the TDC and correlation coefficient. It is further noted that CCF (-1) and CCF (1) have some negative values and all of them have smaller magnitudes. The implication is that an increase of TDC at time t-1 can be associated with an increase or decrease in the correlation coefficient at time t and vice-versa; however, the minimal strength of the positive/negative feedback behavior implies that modeling dynamic conditional correlations by using the DCC method is not able to adequately capture TDC movement. For the 2007-2008 results, we observe stronger lead-lag relationships between the TDCs and correlation coefficients in some cases, but most of the relationships are still very weak. In other words, the correlation coefficients are still not capable of explaining extreme co-movements between the securitized real estate and common stock markets in the longer period, as well as in the two-year GFC periods. Finally, Figure 3 graphs the time series co-movements between the TDCs and correlation coefficients for the eight Asia-Pacific economies.

Table 7   Cross-Correlation Function (CCF) between TDCs and Correlation Coefficients

	Full period (1995-2011)			GFC (2007-2008)		
	CCF(0)	CCF(-1)	CCF(1)	CCF(0)	CCF(-1)	CCF(1)
Australia	0.0688	0.0253	0.0131	0.9955	0.0354	0.0382
China	0.4589	-0.1161	-0.0427	0.2822	0.2242	-0.1116
Hong Kong	0.2334	-0.0832	0.0119	0.1793	0.2424	0.0154
Japan	0.0245	0.0240	-0.0275	0.0259	0.0845	-0.0579
Malaysia	0.0525	0.0205	-0.0069	0.0660	0.0879	0.0975
Philippines	0.0610	0.0901	0.0498	0.9972	-0.0758	-0.1151
Singapore	0.1112	0.0055	0.0015	0.2986	-0.1392	-0.0709
Taiwan	0.0258	-0.0105	0.0912	-0.0057	-0.1203	0.0953

Note: Reported test statistics are cross-correlation values between the TDCs and correlation coefficients of securitized real estate markets and common stock markets. CCF (0) indicates contemporaneous correlation between TDCs and correlation coefficients; CCF (-1) indicates that TDCs caused correlation coefficients at a lag of one-week; CCF (1) indicates that correlation coefficients caused TDCs at a lag of one-week.

In summary, our results reveal that the dynamics of tail dependence between real estate-stock markets are varied across the different country pairs. There are two implications on the tail diversification of portfolios. First, to achieve tail diversification, portfolio managers should diversify among the real estate-stock market pairs in which the tail dependence is low - in our case, to avoid Singapore, the Philippines and Hong Kong, which have the highest extreme real estate-stock market dependence. Second, stronger co-movement of real estate-stock market tail dependence across countries means fewer tail diversification benefits. For example, our findings in Table 6 show that the cross-TDC between China and Hong Kong is very high while the cross-TDCs between Malaysia and China, as well as between Malaysia and Hong Kong, are negative. This implies that the across country tail diversification between the real estate-stock markets can be better achieved by diversifying between China (or Hong Kong) and Malaysia. In other words, portfolio managers can use the TDCs of individual countries and cross-country TDCs to search for appropriate real estate-stock portfolio combinations that hope to achieve maximum tail diversification benefits. Finally, failure to consider the tail dependence between individual real estate–stock tail dependence features, as well as across-country tail dependence in global markets can lead to improper assessment of portfolio extreme risk exposure. The modeling of the tail dependence between real estate-stock returns (as presented in this study) has thus important implications for portfolio risk management in international investing.

Figure 3   Time-series Plots of TDCs and Correlations: Jan 1995-Mar 2011
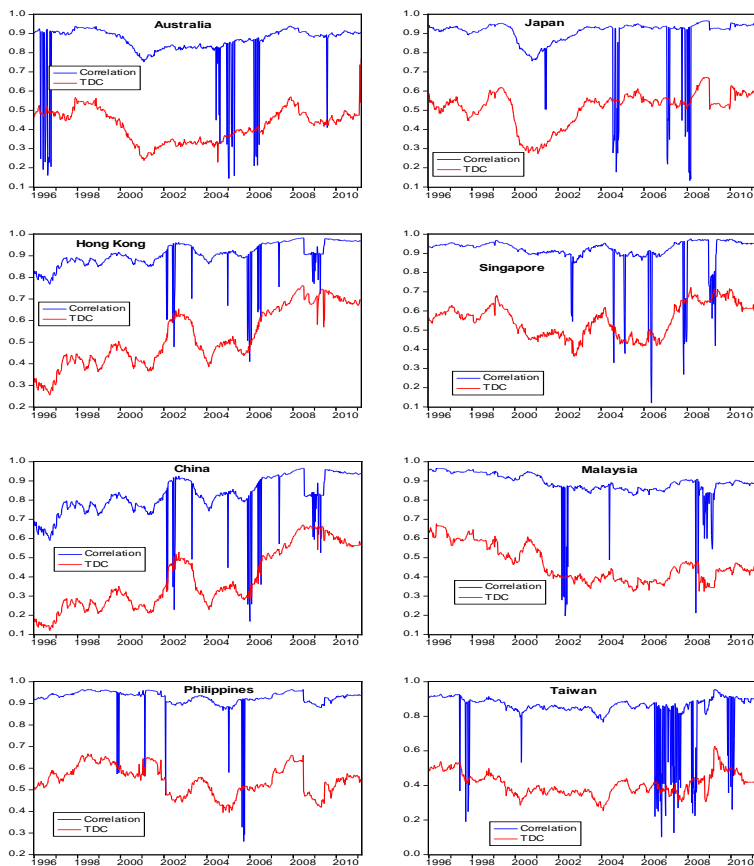
6.   Conclusion

This paper offers two significant contributions towards a better understanding of the relationships between securitized real estate and common stock markets in extreme conditions in eight Asia-Pacific economies over the period of 1995-2011. First, we use the DCC model provided by Engle (2002) to model the dynamic conditional correlations while at the same time extend the model to derive time-varying TDCs. In accordance with the stock market literature, a TDC is particularly useful for studying the extreme dependence between securitized real estate and common stock markets. Second, we study the magnitudes and time-series patterns of individual TDCs, TDC association across eight economies, as well as the lead-lag relationships between the TDCs and correlation coefficients.

Our analysis produces several interesting results subject to the usual empirical caveats: (a) three regions, Singapore, the Philippines and Hong Kong, have the highest extreme real estate–stock market co-movement of at least 50%. Thus, if the average stock (real estate) returns have an extreme movement to a very low level, the probability that the real estate (stock) returns will have an extreme movement on the same week in these three economies is at least 0.5; (b) the TDCs of China, Hong Kong, Japan, the Philippines and Singapore reach their local historical high around the time of the GFC, which imply that during the GFC period, the respective securitized real estate and common stock markets display the highest extreme dependence to react together to financial turmoil. However, all TDCs declined during the post GFC period as the risk attributed to extreme dependence in the domestic economy is reduced; (c) a cross-TDC co-movement analysis indicates that the extreme dependence patterns of real estate-stock markets are similar to those for the majority of the Asian economies. Additional GFC results imply that real estate markets are becoming more integrated with the local stock markets in periods of financial turmoil; (d) lead-lag relationships between TDCs and correlation coefficients are either positive or negative. However, correlation coefficients are not capable of explaining extreme co-movements between the securitized real estate and common stock markets in the longer period, as well as in the two-year GFC periods.   .

To conclude, our comprehensive results provide useful information and advice to international investors and risk management personnel in tactical asset allocation so as to manage the extreme dependence between securitized real estate and common stock markets. More quantitative studies of the extreme dependence of financial markets should receive greater attention.

References

Clayton, J. and Mackinnon, G. (2003). The Relative Importance of Stock, Bond and Real Estate Factors in Explaining REIT Returns, *Journal of Real Estate Finance and Economics,* **27**, 39-60.

Embrechts, P., McNeil, A. and Straumann, D. (2002). "Correlation and Dependency in Risk Management: Properties and Pitfalls" in Dempster, M.A.H. (ed.), *Risk Management: Value at Risk and Beyond* (pp, 176-223), Cambridge: Cambridge University Press

Engle, R. F. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models, *Journal of Business and Economic Statistics*, **20**, 339–350.

Frahm, G. Junker, M. and Schmidt, R. (2005), Estimating the tail-dependence coefficient: Properties and pitfalls, *Insurance: Mathematics and Economics*, **37**, 80-100.

Hoesli, M. and Reka, K. (2011), Volatility Spillovers, Co-movements and Contagion in Securitized Real Estate Markets, Working paper: http://ssrn.com/abstract=1675040

Idzorek, T., Barad, M. and Meier, S. (2006), Commercial Real Estate: the Role of Global Listed Real Estate Securities in a Strategic Asset Allocation, *National Association of Real Estate Investment Trusts.*

Liow, K. H. (2008). Extreme Returns and Value at Risk in International Securitized Real Estate Returns, *Journal of Property Investment and Finance,* **26**, 418-446

Liow, H. K., Ho, K. H. D., Ibrahim, M. F. and Chen, Z. (2009), Correlation and Volatility Dynamics in International Real Estate Securities Markets, *Journal of Real Estate Finance and Economics,* **39**, 202– 223

Lu, C., Wu. S. C. and Ho, L. C. (2009). Applying VaR to REITs: A Comparison of Alternative Methods, *Review of Financial Economics,* **18**, 97-102

McNeil, A. J., Frey, R. and Embrechts, P. (2005). Quantitative Risk Managements: Concepts, Techniques and Tools. Princeton and Oxford: Princeton University Press.

Poon, S. H., Rockinger, M. and Twan, J. (2004). Extreme Value Dependence in Financial Markets: Diagnostics, Models and Financial Applications, *Review of Financial Studies,* **17**, 581-610.

RREEF Research (2007), *Global Real Estate Securities: the Emergence of a Discrete Asset Class.*

So, M. K. P. and Tse, A. S. L. (2009). Dynamic Modeling of Tail Risk: Applications to China, Hong Kong and Other Asian Markets, *Asia-Pacific Financial Markets* DOI 10.1007/s10690-009-9092-6.

Tse, Y. K. and Tsui, A. (2002). A Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model with Time-varying Correlations, *Journal of Business & Economic Statistics,* **20**, 3, 351–363.

Yang, J., Zhou, Y. and Leung W. K., Asymmetric Correlation and Volatility Dynamics among Stock, Bond and Securitized Real Rstate Markets, *Journal of Real Estate Finance and Economics*, DOI 10.1007/s11146-010-9265-0, forthcoming .

Zhou, J. and Gao, Y. (2010). Tail Dependence in International Real Estate Securities Markets, *Journal of Real Estate Finance and Economics* DOI 10.1007/s11146-010-9249-0.

Zhou, J. and Anderson, R. L. (2010). Extreme Risk Measures for International REIT Markets, *Journal of Real Estate Finance and Economics* DOI 10.1007/s11146-010-9252-5.