Increased Tail Dependence in Global Public Real Estate Markets

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Abstract

This study examines the tail dependence of returns in international public real estate markets. By using daily returns of real estate securities in seven countries from 2000 to 2014, we analyze how the interdependence of international securitized real estate markets has changed since the Global Financial Crisis. We divide our sampling period into pre-, during, and post-crisis periods, and estimate both upper and lower tail dependence coefficients for each sub-period. Our empirical results confirm that most country pairs have changed from tail-independent to tail-dependent since 2007. Strong tail dependence persists throughout during crisis and post-crisis periods. The findings from the post-crisis sub-sample provide new evidences on increased tail dependence in global real estate market in recent years. We conclude that international real estate securities still offer diversification benefits nowadays but to a lesser extent than in the pre-crisis period. Investing in global real estate securities markets is beneficial for cross-region, mixed-asset portfolios.

Keywords: tail dependence, real estate investment trust, mixed-assets, real estate, copula

JEL Classification: G11, G15

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1. Introduction

Early studies have established that diversifying into international stock markets offers limited benefits, as global stock markets have been increasingly interdependent. For example, Koch and Koch (1991) found an increase in correlations among daily stock returns from eight countries. Longin and Solnik (1995) examined the correlation of stock returns between the United States and six other countries. They found a significant rise in correlation for four out of six pairs, especially in periods of high volatility. Against this backdrop, securitized real estate gained popularity among investors given their relatively low correlation with other asset classes. International real estate diversification is found to be more effective than international stock and bond portfolios (e.g., Eichholtz, 1996; Hartzell et al., 1986; Liow et al., 2009). This conclusion holds for both mixed-asset portfolios and real-estate-only portfolios (see the review in Worzala and Sirmans, 2003)[1]. Consequently, global public real estate markets expanded remarkably in the last two decades. For example, market capitalization of all US real estate investment trust (REIT) increased from USD 138 billion in 2000 to over USD 907 billion in 2014[2]. As of October 30, 2015, market capitalization of all real estate securities globally is as high as USD 37 trillion[3].

However, as world economies become more integrated, the benefits of diversifying into international real estate markets have been diminishing as well. This trend seems to be more eminent during and after the Global Financial Crisis (e.g., Liow et al., 2015, Zimmer, 2015). Are international real estate markets still offering diversification benefits? If yes, where and how should investors put their money?

To answer these questions, accurately measuring interdependence of return and volatility is essential. The Pearson linear correlation used to be the most popular measurement in this line of research. It also lies in the heart of the capital asset pricing model and the arbitrage pricing theory. However, this approach has received much criticism both from academic researchers and practitioners (e.g., Longin & Solnik, 2001; Rachev et al., 2005) because it assumes that the return series follows a multivariate normal distribution. On the contrary, financial data in real world normally exhibit leptokurtic, skewness, and fat tails (Fama, 1965). As a result, the correlation method usually underestimates the risk of a portfolio and misleads investors to make suboptimal portfolio management decisions.

[1] Similar findings can be found in Echholtz (1996), Okunuv and Wilson(1997), Ling and Naranjo (1999), Okunev et al. (2000), Mei and Hu (2000), Kallberg et al. (2002), Clayton and Machinnon (2003), Wilson and Zurbruegg (2004), Liow and Yang (2005), Michayluk et al. (2006) and Cotter and Stevenson (2006).

[2] Source: https://www.reit.com/data-research/data/us-reit-industry-equity-market-cap.

[3] Source: http://www.ftse.com/Analytics/FactSheets/Home/DownloadSingleIssue?openfile=open&issueName=ENHG

Therefore, this approach should not be used to capture the dependence among financial time series (See evidences in Dowd, 2005; Dulguerov, 2009; and Zhou and Gao, 2012).

To address this issue, researchers have adopted a wide array of alternative methods to measure dependence, including Kendall's τ, Spearman rank correlation, Blomqvist's β, Gini coefficient, and copulas-based methods (Cherubini et al., 2004). Recently, a growing number of studies have highlighted the benefits of using copulas to model dependence structures between financial series. The copula approach, proposed by Sklar (1959), was first introduced in the financial context by Embrechts et al. (1999). It is a flexible function that links univariate marginal distributions to form a joint distribution of these variables (Dowd, 2005) without imposing a multinormal distribution assumption on the underlying variables. Copula models have been widely used in financial studies, including valuating financial derivatives, pricing portfolios and market risk management, and calculating dependence and value-at-risk, because of their simplicity and flexibility (e.g., Chen and Glasserman, 2008; Liu, 2015; Wang and Dyer, 2012; Weiß and Supper, 2013). The method has been found to be particularly beneficial in capturing tail dependence among the time series (Aghakouchak et al., 2010, Chen et al., 2013 and Siburg et al., 2015).

Tail dependence is a measurement of the probability of a joint movement of two or more time series under extreme market conditions (e.g., boom or bust). It can describe the chance of observing the extreme value of one asset (market) given that the other asset (market) shows an extreme value during market downturns and upturns. The analysis is more relevant and useful to understand the co-movement between two or more real estate markets during stressful times (Muns and Bijlsma, 2015). Considering that the focus of our study is to investigate whether and how the interdependence of international real estate markets has changed since the Global Financial Crisis, we adopt the copula method to model the underlying distribution of returns accurately.

The copula method has been used in real estate literature with promising results. For example, significant tail dependence has been identified in regional and international securitized real estate markets (Knight et al., 2005; Zhou and Gao 2012; Hoesli and Reka, 2013). Evidence shows that copula estimates are superior to those of the CCC-GARCH and DCC-GARCH models (Zhou and Gao, 2012), and that the distribution of securitized real estate returns is neither normal nor symmetric (Hoesli and Reka, 2013). Following this line of practice, we adopt the copula method in our investigation of tail dependence in international public real estate securities markets.

The closest existing studies to our work is Zhou and Gao (2012) and Hoesli and Reka (2013), where tail dependence in real estate securitized markets are analyzed by using dynamic Copula estimator. However, Zhou and Gao (2012) used data from 2000 to 2009, and Hoesli and Reka (2013) used data for the U.S., the U.K. and Australia for the period 1990–2010 only. Neither of them had sufficient data to analyze tail dependence in real estate returns after the Global

Financial Crisis. Yet, findings from this period (i.e., from 2010 onwards) are most relevant for investors. To bridge this gap in the literature, we extend their work by including data from 2000 to 2014 to provide new evidences on tail dependence in the post-crisis period. We divide the whole sampling period into pre-crisis, during crisis, and post-crisis sub-periods, for which the coefficients of upper and lower tail dependence are estimated to illustrate the effect of a financial crisis. The analysis is carried out by using data from seven countries from the American, Asia-Pacific, and European regional markets.

The main finding is that tail dependence in international public real estate securities market has increased notably since the Global Financial Crisis. Almost all tail-independent country-pairs have changed to tail-dependent. This pattern is consistent for the interdependence between stock market and both domestic and international real estate securities markets. Real-estate-only portfolios are more affected than mixed-asset portfolios. Although our analysis shows that diversifying into international real estate markets is still beneficial, the gains of such an approach have significantly reduced during the financial crisis, and the trend has not been reverted or even stopped during the post-crisis period. The findings from the post-crisis sub-sample provide new evidences on increased tail dependence in global real estate market in recent years.

2. Methodologies

Our estimation strategy involves three stages. First, we use a AR(1)-GJR-GARCH(1,1) model (Glosten et al., 1993) to filter the returns to obtain their corresponding residual series. AR-GJR models can capture asymmetric effects on the volatility between two time series, i.e., negative innovations to the returns may generate higher volatility than positive innovations of the same magnitude (Gordon and Canter, 1999, Cotter and Stevenson, 2006; Michayluk et al., 2007).

Second, we estimate the marginal distribution from the residuals obtained in the first step non-parametrically through their empirical cumulative distribution. This procedure is routine to prepare the estimated residual series for the copula estimation in the next step. Specifically, copula models require the inputs to be uniformly distributed within the [0,1] range. To meet this requirement, the marginal distribution of residuals is estimated using the following formula:

$$F_i(x_i) = \frac{1}{T+1}\sum_{t=1}^{T} 1_{\{x_{i,t} \le x_i\}} \tag{1}$$

where $1_{\{x_{i,t} \le x_i\}}$ is an indicator function that takes the value of one if the argument is true and zero otherwise.

Finally, we use the copula method to link the univariate marginal distributions derived from previous steps. A wide range of copula functions is available, as discussed by Joe (1997) and Nelsen (2007). Among these candidates, Gaussian and *t* copula functions are the most commonly used, although they are not without shortcomings. Gaussian copula does not enable tail dependence, while t copula only considers symmetric tail dependence. Both models are not flexible enough for the purpose of our analysis. Therefore, we adopt the SJC copula (Patton et al., 2006), which is a modification of the Joe–Clayton copula of Joe (1997), as this model can provide both upper and lower tail dependence coefficients to quantify the degree of tail dependences.

For simplicity, we use a bivariate case to illustrate the method adopted in this study. For two uniformly distributed residual series X and Y with a marginal distribution function of $u = F_x(x), v = F_y(y)$, their joint distribution defined by the SJC copula is $F(x,y) = C(u,v)$. If both marginal distributions are continuous, then the copula C_{SJC} is uniquely defined as follows[4]:

$$C_{SJC}(u,v) = F\left(F_x^{-1}(u), F_y^{-1}(u)\right). \quad (2)$$

Tail dependence is measured by an upper tail dependence coefficient, τ^U, and a lower tail dependence coefficient, τ^L, as given in Equations (3) and (4).

$$\tau^U = \lim_{\xi \to 1} P\left(u > \xi \middle| v > \xi\right) = \lim_{\xi \to 1} P\left(v > \xi \middle| u > \xi\right) = \lim_{\xi \to 1}\left(1 - 2\xi + C(\xi,\xi)\right)/(1-\xi) \quad (3)$$

$$\tau^L = \lim_{\xi \to 0} P\left(u \le \xi \middle| v \le \xi\right) = \lim_{\xi \to 0} P\left(v \le \xi \middle| u \le \xi\right) = \lim_{\xi \to 0} C(\xi,\xi)/\xi \quad (4)$$

where $\tau^U \in [0,1], \tau^L \in [0,1]$. When $\tau^U = 0\left(\tau^L = 0\right)$, the upper (lower) tail dependence is absent.

The tail dependence coefficients in (3) and (4) are constant over time. This could be problematic for studies with long sampling period. To capture the evolution of the tail dependences, we adopt the time-varying SJC copula proposed by Patton (2006), in which the tail parameters are defined in equation (5) and (6). This approach is also used in Zhou and Gao (2012) and Hoesli and Reka (2013).

$$\tau_t^L = \Lambda\left(\omega_L + \beta_L \tau_{t-1}^L + \alpha_L \cdot \frac{1}{10}\sum_{j=1}^{10}\left|u_{t-j} - v_{t-j}\right|\right) \quad (5)$$

$$\tau_t^U = \Lambda\left(\omega_U + \beta_U \tau_{t-1}^U + \alpha_U \cdot \frac{1}{10}\sum_{j=1}^{10}\left|u_{t-j} - v_{t-j}\right|\right) \quad (6)$$

where $\Lambda(x) \equiv (1+e^{-x})^{-1}$ is the logistic transformation to constraint the tail dependences to stay in (0,1).

3. Data

We collect daily price indices on publicly traded real estate securities and stocks from seven markets from the Thomson Reuters DataStream. The seven markets,

[4] The specific expression of C_{SJC} is $C_{SJC}(u,v|\tau^U,\tau^L) = 0.5\cdot(C_{JC}(u,v|\tau^U,\tau^L) + C_{JC}(1-u,1-v|\tau^U,\tau^L) + u + v - 1)$, where $C_{JC}(u,v|\tau^U,\tau^L) = 1-(1-\{[1-(1-u)^k]^{-\gamma} + [1-(1-v)^k]^{-\gamma} - 1\}^{-1/\gamma})^{1/k}$.

namely, the United States, Hong Kong, Japan, Australia, Singapore, the United Kingdom, and France, are further grouped into three regional markets (i.e., America, Asia-Pacific, and Europe). The sample covers the most important securitized real estate markets in the world, as indicated by both the market capitalization and the history of securitized real estate market in each country. As shown in Table 1, all countries except for the United Kingdom have their first REITs listed at least a decade ago. The total capitalization of REIT markets exceeds USD 100 billion in all countries, thus signifying the importance of the real estate sector in the national economy. On the whole, the sample is a good representation of global securitized real estate markets. The common stock market and public real estate market indices used in this study are also given in Table 1.

Our sample consists of approximately 3,850 daily observations of real estate and stock price indices from March 31, 2000 to December 31, 2014. We define the return of the price index in market *i* at time *t* as $R_{i,t} = 100 \cdot (P_{i,d} - P_{i,t-1}) / P_{i,t-1}$, where $P_{i,d}$ denotes the daily price of the price index.

[Insert Table 1 here]

The summary statistics of the returns for the whole sampling period is presented in panel A of Table 2. Mean daily returns vary across all the seven countries, ranging from as low as 0.0046 in Australia to as high as 0.0480 in Japan. The returns show significant skewness and kurtosis, i.e., the tails are fat and asymmetric in all countries. The Jarque–Bera normality test also rejects the null hypothesis that the returns follow the Gaussian distribution. These results lead to the adoption of non-Gaussian models to describe the marginal distributions of and the dependence structures between these countries.

Figure 1 presents the movement of daily prices of the seven countries. Daily prices in different countries tend to move in similar directions and fluctuate dramatically during in last financial crisis (2007–2009), but the patterns are less consistent after 2009. The dependence structures among the countries might have changed since the Global Financial Crisis. Therefore, in the latter parts of the paper, we investigate this change in dependence by dividing the whole period into three sub-periods: pre-crisis (2000–2006), during crisis (2007–2009), and post-crisis (2010–2014) period. The descriptive statistics of these three sub-samples are given in panels B to D in Table 2. In general, the during crisis period has the lowest returns compared with those in the other two periods. Conversely, the standard deviations of the daily return of the real estate indices of all countries are the largest, i.e., they are most volatile in the crisis period.

[Insert Table 2 here]

[Insert Figure 1 here]

4. Empirical Findings

We first filter the return series of real estate securities with the AR(1)-GJR-GARCH(1,1) model to obtain the *i.i.d.* residuals, which are used to construct the marginal distributions for returns in the next stage. The estimated results from the filter are shown in Table 3. The parameter used to describe the asymmetry effect (i.e., γ) is significant at the 5% level for almost all countries in all sub-periods, thus indicating that the securitized real estate indices are more sensitive to negative news than to positive news. Moreover, the estimated γ in the during crisis period (i.e., Panel B in Table 3) is much larger than that in other sub-periods. All preliminary evidence suggests that the fatness and asymmetry of tails should be considered in the steps to follow.

[Insert Table 3 here]

4.1 Real-Estate-Only Analysis

In this section, we present results that are relevant to real-estate-only portfolio management. Specifically, we estimate the tail dependence between the real estate securities market and country pairs. With residuals obtained from the previous step, we construct the marginal distributions of the returns through empirical cumulative distribution estimation. The results are then linked by SJC copula functions to estimate the tail dependence coefficients as defined in Equations (3) and (4). With the seven countries included in our sample, we obtain 21 country pairs. In order to verify that SJC copula is a better estimator than Gaussian Copula, we compare the AIC statistics between these two models in the last two columns of Table 4. Except for two tail-independent country-pairs (i.e., US-Japan and US-Singapore), all other country-pairs have smaller AIC values in their SJC Copula models. We therefore use SJC Copula estimator in the rest of the analysis.

Table 4 also gives tail dependence coefficients estimated from the static SJC Copula. These are tail dependence measurements over the entire sampling period. The results suggest that US and Asia-Pacific real estate markets are tail independent, whilst most of other country-pairs are both upper- and lower-tail dependent. There are a few exceptions such as HK-France, Japan-France and Australia-France that are lower-tail dependent only. The results need to be interpreted with caution, as static SJC Copula does not take into account the dynamics of tail dependence over time. We further explore this issue by firstly analyzing data by sub-periods, and then by estimating dynamic tail dependence coefficients.

[Insert Table 4 here]

Table 5 reports tail dependence coefficient estimates by sub-periods. Several conclusions can be drawn from Table 5. First, the number of country pairs that exhibit tail dependence increases significantly during the Global Financial Crisis (12 and 15 pairs showing upper tail and lower tail dependence, respectively; see the last row in Table 5) compared with the number before 2007 (with only two pairs with upper tail dependence and four pairs with lower tail dependence). This pattern remains largely unchanged during the post-crisis period. The number of country pairs with lower tail dependence even increases to 19. Therefore, we conclude that the financial turmoil exerts a significant and long-lasting effect on the dependence structures among countries. The international real estate securities market used to be a good diversification vehicle, as suggested by the low tail dependence coefficients for the period of 2000 to 2006. However, these diversification benefits decreased notably since 2007. Surprisingly, a significant increase in country pairs with lower tail dependence is observed. As diversification matters the most during market downturns, our findings suggest that most international securitized real estate markets cannot offer the same level of protection now as they did in the pre-2006 period.

[Insert Table 5 here]

However, the picture is not completely gloomy. Specifically, not all countries are affected by the financial crisis equally. For example, tail dependences between the United States and other countries are insignificant even during the turmoil, consistent with the results in Zhou and Gao (2012). In addition, the tail dependence among European countries (as high as 0.5362 and 0.6095 for the upper and lower tail dependence, respectively, during the crisis) is much stronger than that among Asian countries. We also observe a closer relationship among countries in the same continent than the country pairs belonging to different continents. For example, the coefficients of UK–France pair in all three periods are much larger than the corresponding coefficients of the UK–HK pair. Identifying the causes of these differences is beyond the scope of this study, as the focus of this study is to investigate whether and how tail dependence among countries varies over time and across geographic regions. Our findings strongly support the notion that interdependence among international securitized real estate markets is complex and dynamic. We conclude that the landscape of international securitized real estate markets in terms of tail dependence has changed fundamentally since the Global Financial Crisis. Markets are much more dependent on each other, especially during difficult times. Although the global economy has been gradually recovering from the crisis, strong tail dependence (lower tail dependence in particular) still persists. Investors and fund managers should take this into account when considering international securitized real estate products in their portfolios.

The findings in Table 5 are interesting and informative. However, the definition of sub-periods is subjective, and might introduce errors in the analysis. For example, one may wonder if it is necessary to split the 2007 to 2014 period into during- and post- crisis sub-periods. To answer this question, we use a time-varying Copula estimator as defined in Equation (5) and (6) to re-estimate the tail dependence coefficients for all country pairs with at least one tail dependence.

As the data are daily series, the original coefficient estimate series are quite noisy. In order to show the trend clearly, we smooth the estimates by using a 250-day rolling window[5]. The time-varying lower and upper tail dependences for each country-pair are presented in Figure 2. The patterns identified in this Figure are very similar to those in Table 5. For example, tail dependence has increased on the whole; within-region tail dependence is stronger than cross-region ones; and HK-Singapore and UK-France have the strongest tail dependence throughout the whole sampling period.

More importantly, Figure 2 reveals two peaks in lower-tail dependence in the 2008-2009 and 2011-2012 periods for most country-pairs. These could be attributed to the Global Financial Crisis and the European Debt Crisis, with an approximately one-year lag time. This is consistent with existing findings that negative shocks have significant impacts on the linkages between different real estate markets. It is worth noting that the pattern is not restricted to EU countries. For example, the Australian-Singapore and HK-Japan pairs also demonstrated this bi-modal pattern. Although we cannot be certain about the cause of the second peak around 2011 and 2012, there was not a global event that is equivalent to the Global Financial Crisis during that period of time. Yet the level of lower-tail dependence increased with almost the same magnitude. This indicates that global real estate markets have become more interdependent since the Global Financial Crisis. The findings justify our strategy to analyze tail dependence by sub-periods. We continue to use the three sub-period approach in the rest of the analysis. This is because it provides similar results as dynamic Copula approach, but with more intuitive and economically meaningful interpretations.

[Insert Figure 2 here]

[5] We choose 250 as the window size of smoothing so that each point represents the tail dependence in one year. We have also tried other window size, but found they made little differences.

4.2 *Mixed Assets Analysis*[6]

Our findings in Table 5 shed some light on the investment strategies for real-estate-only portfolios. The benefits of diversifying into international real estate securities markets diminished significantly since 2007. Is the same conclusion also true for mixed-asset portfolios? To answer this question, we analyze the tail dependence between stock markets and securitized real estate markets both at the domestic and international levels.

For each of the seven countries, we first estimate the tail dependence coefficients between its own stock market and the real estate securities market. The results are given in Table 6. Unsurprisingly, stocks and publicly traded real estate securities are significantly related throughout the period for all countries. Both upper tail and lower tail coefficients increase since the financial crisis in all countries except for Hong Kong. The conclusion is that the returns of the two asset classes are highly correlated within a country, especially during and after the financial crisis.

This picture changes when we investigate the tail dependence between the returns of stocks in each country and the returns of real estate securities in other countries. We estimate the upper tail and low tail dependence coefficients for 42 country pairs formed among the seven countries under investigation. The results are presented in Table 7.

[Insert Table 6 here]

[Insert Table 7 here]

Similar to the pattern identified in Tables 5 and 6, the link between domestic stock market and international real estate also became closer since the beginning of the financial turmoil. This result can be justified by the increase in country-pairs that exhibit tail dependence. However, two aspects deserve further discussion. First, the level of tail dependence in Table 7, as measured by the absolute values of tail dependence coefficients, is much smaller than that in Table 6. This finding indicates that investing in international real estate securities markets still offers significant diversification benefits compared with investing in domestic real estate securities market. Second, although the interdependence between domestic stock market and international real estate securities markets increased during the financial crisis, the magnitude of changes is smaller than that reported in Table 5. For example, in Table 6, the number of country-pairs

[6] Dynamic SJC Copula estimates show similar patterns as identified in Table 6 and Table 7. Therefore, the results are not presented here, but available from the author upon requests.

with significant upper tail dependence actually drops from 29 in the during crisis period to 25 in the post-crisis period, while the same statistics is maintained in Table 5. The increase in country-pairs with lower tail dependence is also much smaller after 2007 in Table 6 than in Table 5.

In conclusion, diversification benefits can still be gained by investing across asset classes and geographic regions, although the advantages have significantly reduced during and after the financial crisis. Generally, investors are recommended to form mixed-asset portfolios that consist of both stocks and real estate securities from different geographic regions. Real-estate-only portfolios, regardless of how geographically distributed, cannot offer enough diversification benefits as they did before the Global Financial Crisis. This finding is particularly true when markets are under the influence of negative shocks.

5. Conclusion

We study the dependence structures in seven major public real estate markets (i.e., the United States, Hong Kong, Japan, Australia, Singapore, the United Kingdom, and France). A flexible form of the copula model, i.e., the SJC copula, is adopted to quantify the tail dependence in the return series. In contrast to previous studies that evaluated only long-run correlation or dependence of real estate markets, we model the changes of dependence between country-pairs using three subsamples that cover the pre-, during, and post-Global Financial Crisis periods. This is an extension of Zhou and Gao (2012) and Hoesli and Reka (2013) by emphasizing international linkages and by using sub-periods to investigate whether tail dependence changes over time. The findings from the post-crisis sub-sample provide new evidences on increased tail dependence in global real estate market in recent years. Our empirical results confirm that a large number of country-pairs have changed from tail independence to tail dependence since the crisis. The benefits of diversifying into international real estate securities markets have significantly decreased, especially for real-estate-only portfolios.

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Table 1: Market capitalization and the history of REITs market

Country	Size of REITs market (US $ million, FTSE)	First REITs Listed	Public Real Estate Market Index	Stock Market Index
US	529265	1960	FTSE/NAREIT ALL REITs Index	S&P 500
HK	14966	2003	Hang Seng Property Index	Hang Seng Index
Japan	63701	2000	Topix Real Estate Index	Nikkei 225
Australia	63692	1971	S&P /ASX 300 Real Estate Index	S&P/ASX 200
Singapore	10911	2002	FTSE Singapore Real Estate Index	Straits Times Index
UK	49319	2007	FTSE 350 Real Estate Index	FTSE 100
France	18950	2003	FTSE France REITs Index	France CAC 40

Table 2 Descriptive statistics of daily returns (real estate securities)

Panel A Whole period (2000–2014)

	US	HK	Japan	Australia	Singapore	UK	France
Mean	0.0404	0.02986	0.0479	0.0045	0.0331	0.0253	0.0290
Max	17.629	14.4702	17.7484	7.6359	9.1919	9.5305	6.1230
Min	-18.57	-11.1328	-13.2078	-10.5163	-8.6871	-9.6150	-6.0813
Std	1.8658	1.8204	2.1488	1.2246	1.3075	1.4230	1.0304
Skewness	0.3731	0.3303	0.2004	-0.6543	0.1413	-0.0375	-0.1966
Kurtosis	21.812	7.5482	7.0070	13.2809	8.0811	9.1407	7.6408
Normality	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Panel B Pre-crisis period (2000–2006)

	US	HK	Japan	Australia	Singapore	UK	France
Mean	0.0564	0.0262	0.0822	0.0365	0.0653	0.0702	0.0655
Max	4.6191	7.6881	9.6785	3.9325	6.3031	8.9284	5.4816
Min	-5.1945	-8.8901	-6.9281	-3.4232	-7.5903	-5.3814	-3.8550
Std	0.8570	1.5982	1.8534	0.6553	1.2371	0.9338	0.6960
Skewness	-0.4487	0.1707	0.2563	0.0456	-0.0603	0.3492	-0.1416
Kurtosis	5.9255	5.5681	4.3440	5.1794	5.7933	11.2895	8.7306
Normality	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Panel C During crisis period (2007–2009)

	US	HK	Japan	Australia	Singapore	UK	France
Mean	-0.0108	0.0620	-0.0673	-0.1032	-0.0035	-0.1007	-0.0460
Max	17.6291	14.4702	17.7485	7.6360	9.1919	9.5305	5.3098
Min	-18.5702	-11.1328	-11.2621	-10.5163	-8.6871	-9.6150	-6.0814
Std	3.5900	2.7279	2.9812	2.2291	1.9664	2.4354	1.5719
Skewness	0.3071	0.3565	0.2344	-0.4229	0.3129	0.0480	-0.0653
Kurtosis	7.5610	5.2808	5.5323	5.5615	5.5006	4.2245	4.2685
Normality	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Panel D Post-crisis period (2010–2014)

	US	HK	Japan	Australia	Singapore	UK	France
Mean	0.0497	0.0156	0.0711	0.0262	0.0118	0.0405	0.0250
Max	9.7301	8.5714	11.7676	4.0699	3.1235	5.7879	6.1230
Min	-8.7683	-5.9367	-13.2078	-3.3336	-3.6517	-5.2746	-5.6244
Std	1.2457	1.3678	1.9117	0.9264	0.8119	1.1093	0.9968
Skewness	0.0593	0.1141	0.1519	0.1219	-0.4528	0.0098	-0.1450
Kurtosis	10.3782	5.6805	8.3050	4.2981	5.3105	6.4630	7.0493
Normality	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Note: Means are in percentage. Normality is the p-value of the Jarque−Bera test.

Table 3 Estimation results from the AR(1)- GRACH(1,1) model

Panel A Pre-crisis period (2000–2006)

	US	HK	Japan	Australia	Singapore	UK	France
c	0.0550*	0.0243	0.0780*	0.0317*	0.0861*	0.0823*	0.0823*
s	0.0767*	0.1062*	0.1328*	0.0028	-0.0217	--	--
ω	0.0382*	0.0214*	0.0584*	0.0230*	0.1304*	0.0224*	0.0652*
α	0.8330*	0.9479*	0.9123*	0.8847*	0.8093*	0.8939*	0.7255*
β	0.0680*	0.0205*	0.0557*	0.0405*	0.1027*	0.0444*	0.0689*
γ	0.0918*	0.0485*	0.0349*	0.0450*	0.0117	0.0775*	0.1353*

Panel B During crisis period (2007–2009)

	US	HK	Japan	Australia	Singapore	UK	France
c	-0.0581	0.0070	-0.1025	-0.0342	-0.0122	-0.1219	-0.0265
s	-0.1519*	--	--	0.0206	0.0560	--	0.0645
ω	0.0501	0.0810*	0.0870*	0.1116*	0.0202	0.0599*	0.0769*
α	0.8945*	0.8984*	0.9275*	0.8137*	0.9072*	0.9107*	0.8503*
β	0.0414*	0.0429*	0.0173	0.0897*	0.0428*	0.0628*	0.0851*
γ	0.1282*	0.1037*	0.0977*	0.1685*	0.0974*	0.0380	0.0747*

Panel C Post-crisis period (2010–2014)

	US	HK	Japan	Australia	Singapore	UK	France
c	0.0554*	-0.0043	0.0539	0.0382	0.0136	0.0390	0.0165
s	-0.0417	0.1079*	0.0853*	-0.0685*	0.0281	--	0.1039*
ω	0.0187*	0.0135*	0.1532*	0.0170*	0.0095*	0.0353*	0.0215*
α	0.8839*	0.9678*	0.8652*	0.9198*	0.9371*	0.8978*	0.9030*
β	0.0590*	0.0019	0.0551*	0.0224	0.0125	0.0011	0.0009
γ	0.0865*	0.0452*	0.0837*	0.0729*	0.0638*	0.1432*	0.1467*

Note: c, s, ω, α, β, and γ are parameters in our AR (1)-GARCH (1,1) model that is specified as $r_{it} = c_i + s_i \cdot r_{it-1} + \varepsilon_{it}$, $\varepsilon_{it} = h_{it} \cdot z_{it}$, $z_{it} \sim N(0,1)$, and $h_{it}^2 = \omega_i + \alpha_i \cdot \varepsilon_{it-1}^2 + \beta_i \cdot h_{it-1} + \gamma \cdot \varepsilon_{it-1}^2 \cdot I_{\{\varepsilon_{it}<0\}}$. We use Ljung-Box test to check whether a time series is auto-correlated. If the null hypothesis of 'non-autocorrelation' is not rejected, the autocorrelation component will be dropped from the AR (1)-GARCH (1,1) model, and the value of s will be marked with '--' in the table.

* denotes significance at the 5% level.

Table 4 Comparison estimated results from SJC Copula and Gaussian Copula

		Upper Tail coefficient	Lower Tail coefficient	AIC(SJC)	AIC(Gaussian)
US	HK	0.0005	0.0157	-40.3564	-36.7922
	Japan	0.0001	0.0001	-2.7904	-5.5274
	Australia	0.0001	0.0060	-17.6222	-16.9850
	Singapore	0.0056	0.0233	-64.0882	-65.0472
	UK	0.0982*	0.1368*	-339.5978	-328.4002
	France	0.0805*	0.1144*	-285.1623	-274.3410
HK	Japan	0.0832*	0.2084*	-449.7728	-423.5952
	Australia	0.0690*	0.1373*	-311.7764	-309.7874
	Singapore	0.2510*	0.3896*	-1257.7995	-1230.1942
	UK	0.0373*	0.1403*	-262.5404	-221.4440
	France	0.0184	0.1444*	-247.5085	-230.8396
Japan	Australia	0.0593*	0.1480*	-310.4317	-292.6116
	Singapore	0.0460*	0.2470*	-480.8170	-430.6554
	UK	0.0210	0.0830*	-162.4419	-151.0918
	France	0.0054*	0.0939*	-154.9263	-146.4446
Australia	Singapore	0.0684*	0.1720*	-368.0296	-350.2484
	UK	0.0565*	0.0472*	-137.6837	-129.3188
	France	0.0282	0.0531*	-133.4869	-132.6678
Singapore	UK	0.0426*	0.1823*	-343.9178	-313.5506
	France	0.0464*	0.1735*	-339.0860	-303.7674
UK	France	0.3342*	0.4395*	-1662.1857	-1550.8330

* denotes significance at the 5% level.

Table 5 Tail dependence estimation by sub-periods

		Pre-crisis (2000–2006)		During crisis (2007–2009)		Post-crisis (2010–2014)	
		Upper tail	Lower tail	Upper tail	Lower tail	Upper tail	Lower tail
US	HK	0.0001	0.0055	0.0282	0.0014	0.0043	0.0582*
	Japan	0.0001	0.0001	0.0001	0.0104	0.0036	0.0001
	Australia	0.0001	0.0001	0.0017	0.0015	0.0001	0.0591
	Singapore	0.0004	0.0003	0.0163	0.0700	0.0237	0.0894*
	UK	0.0398	0.0205	0.1155*	0.2732*	0.2318*	0.2115*
	France	0.0165	0.0002	0.1245*	0.2674*	0.2135*	0.2166*
HK	Japan	0.0221	0.1424*	0.1864*	0.3260*	0.1385*	0.2184*
	Australia	0.0260	0.0252	0.1510*	0.3236*	0.0901*	0.1791*
	Singapore	0.1833*	0.2735	0.3625*	0.5366*	0.2898*	0.4365*
	UK	0.0072	0.1206	0.0849	0.1219*	0.0598	0.1785*
	France	0.0001	0.1056	0.0805	0.1972*	0.0741*	0.1525*
Japan	Australia	0.0037	0.0387	0.1726*	0.3222*	0.1205*	0.1913*
	Singapore	0.0001	0.1818	0.2245*	0.3546*	0.1064*	0.2497*
	UK	0.0031	0.0365	0.0345	0.1443*	0.0493	0.0923*
	France	0.0001	0.0540	0.0198	0.2028*	0.0354	0.0695*
Australia	Singapore	0.0105	0.0552*	0.1618*	0.2771*	0.1357*	0.2552*
	UK	0.0296	0.0001	0.1129*	0.0601	0.0364	0.1064*
	France	0.0154	0.0016	0.0958*	0.0805	0.0150	0.1126*
Singapore	UK	0.0114	0.1273*	0.0899	0.1939*	0.0805*	0.2418*
	France	0.0001	0.1024	0.1120*	0.2740*	0.1105*	0.2186*
UK	France	0.0770*	0.2524*	0.5362*	0.6095*	0.5335*	0.5212*
Number of significant pairs		2	4	12	15	12	19

* denotes significance at the 5% level.

Table 6 Dependence between stock and public real estate markets at the national level

	Pre-crisis		During crisis		Post-crisis	
	upper tail	lower tail	upper tail	lower tail	upper tail	lower tail
US	0.3925*	0.3351*	0.5785*	0.6862*	0.5391*	0.5687*
HK	0.6895*	0.7046*	0.6242*	0.7612*	0.6235*	0.6930*
Japan	0.4243*	0.5339*	0.4799*	0.6537*	0.4913*	0.6467*
Australia	0.3080*	0.3236*	0.4024*	0.5564*	0.4119*	0.5077*
Singapore	0.3613*	0.4910*	0.6401*	0.7236*	0.5598*	0.6791*
UK	0.1911*	0.4062*	0.4267*	0.5470*	0.5176*	0.5413*
France	0.0388	0.1696*	0.4062*	0.5813*	0.5230*	0.5170*
Number of significant pairs	6	7	7	7	7	7

* denotes significance at the 5% level.

Table 7 Dependence between stock and public real estate markets at the international level

		Pre-crisis		During crisis		Post crisis	
Stock	RE	upper tail	lower tail	upper tail	lower tail	upper tail	lower tail
US	HK	0.0007	0.0465	0.0947*	0.0209	0.0296	0.0601
	Japan	0.0001	0.0002	0.0001	0.0431	0.0049	0.0019
	Australia	0.0001	0.0001	0.0059	0.0013	0.0001	0.0163
	Singapore	0.0001	0.0230	0.1010*	0.0681	0.0500	0.0877*
	UK	0.0785	0.0982*	0.1428*	0.3286*	0.3213*	0.2435*
	France	0.0166	0.0173	0.1584*	0.3749*	0.3553*	0.2467*
HK	US	0.0001	0.0172	0.0400	0.0069	0.0002	0.0705*
	Japan	0.0568	0.1720*	0.1877*	0.3828*	0.1558*	0.2749*
	Australia	0.0739	0.0346	0.1703*	0.3183*	0.1136*	0.2530*
	Singapore	0.2166*	0.3242*	0.4730*	0.5314*	0.2626*	0.4589*
	UK	0.0291	0.1220*	0.1430*	0.1148*	0.0732*	0.2543*
	France	0.0001	0.1347	0.1671*	0.1993*	0.0439	0.2272*
Japan	US	0.0001	0.0001	0.0003	0.0133	0.0058	0.0002
	HK	0.1503*	0.2543*	0.2085*	0.4722*	0.1579*	0.2379*
	Australia	0.0228	0.0745*	0.1889*	0.3685*	0.0691	0.2777*
	Singapore	0.0145	0.2609*	0.2248*	0.4714*	0.1152*	0.3036*
	UK	0.0234	0.0600*	0.0407	0.1537*	0.0554	0.1292*
	France	0.0001	0.0761	0.0703	0.2045*	0.0105	0.1359*
Australia	US	0.0001	0.0001	0.0416	0.0015	0.0137	0.0223
	HK	0.1435*	0.2328*	0.3494*	0.4757*	0.1995*	0.3625*
	Japan	0.0646*	0.1608*	0.2535*	0.4252*	0.2211*	0.3036*
	Singapore	0.0473	0.2287*	0.3107*	0.4373*	0.2056*	0.3813*
	UK	0.0174	0.0571*	0.0967*	0.1265*	0.0998*	0.1874*
	France	0.0001	0.0754	0.0805	0.1859*	0.0451	0.1771*
Singapore	US	0.0001	0.0182	0.0250	0.0714	0.0373	0.0629
	HK	0.2146*	0.3851*	0.3942*	0.5732*	0.3091*	0.4551*
	Japan	0.0067	0.2069*	0.2140*	0.3529*	0.0934*	0.2774*
	Australia	0.0201	0.0863*	0.1148*	0.2660*	0.1043*	0.2811*
	UK	0.0073	0.1657*	0.1614*	0.2125*	0.1150*	0.2532*
	France	0.0001	0.1589	0.1993*	0.3200*	0.1111*	0.2215*
UK	US	0.1372*	0.0528	0.2206*	0.2730*	0.2127*	0.2806*
	HK	0.0498	0.1490*	0.1683*	0.2164*	0.0893*	0.1937*
	Japan	0.0002	0.0763*	0.0301	0.1887*	0.0368	0.0598
	Australia	0.0222	0.0058	0.0717	0.0578	0.0290	0.0676*
	Singapore	0.0083	0.1506*	0.1923*	0.2557*	0.0982*	0.2217*
	France	0.0339	0.1499*	0.4138*	0.5487*	0.4665*	0.4257*
France	US	0.1245*	0.0917*	0.2106*	0.3274*	0.2431*	0.2860*
	HK	0.0807*	0.1198*	0.1870*	0.1895*	0.0984*	0.1458*
	Japan	0.0003	0.0867*	0.0200	0.2079*	0.0345	0.0345
	Australia	0.0045	0.0268	0.0667	0.0710	0.0050	0.0609*
	Singapore	0.0191	0.1608*	0.1891*	0.2577*	0.0818*	0.1945*
	UK	0.1447*	0.3298*	0.3591*	0.5391*	0.4715*	0.4640*
Number of significant pairs		9	25	29	31	25	33

* denotes significance at the 5% level.

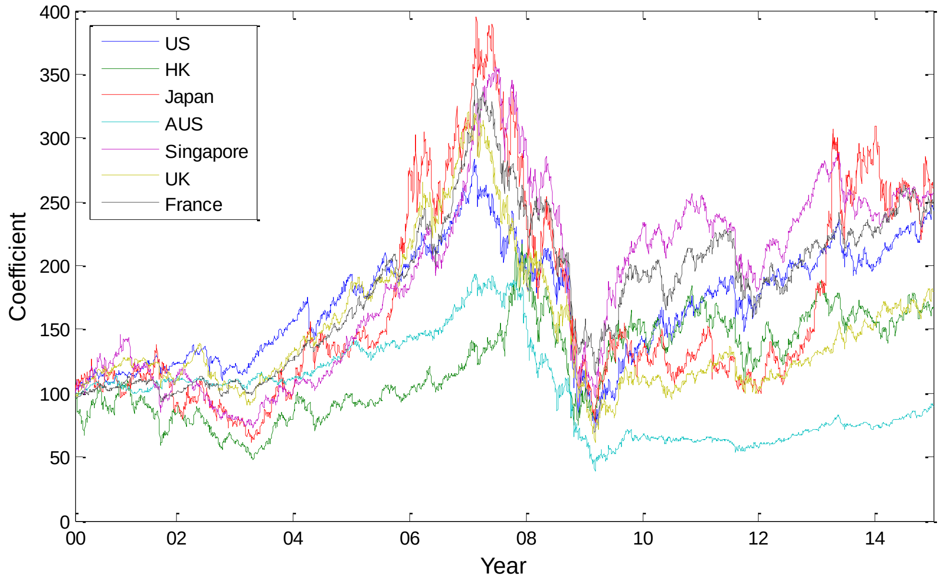

Figure 1 Securitized real estate price indices (2000–2015)

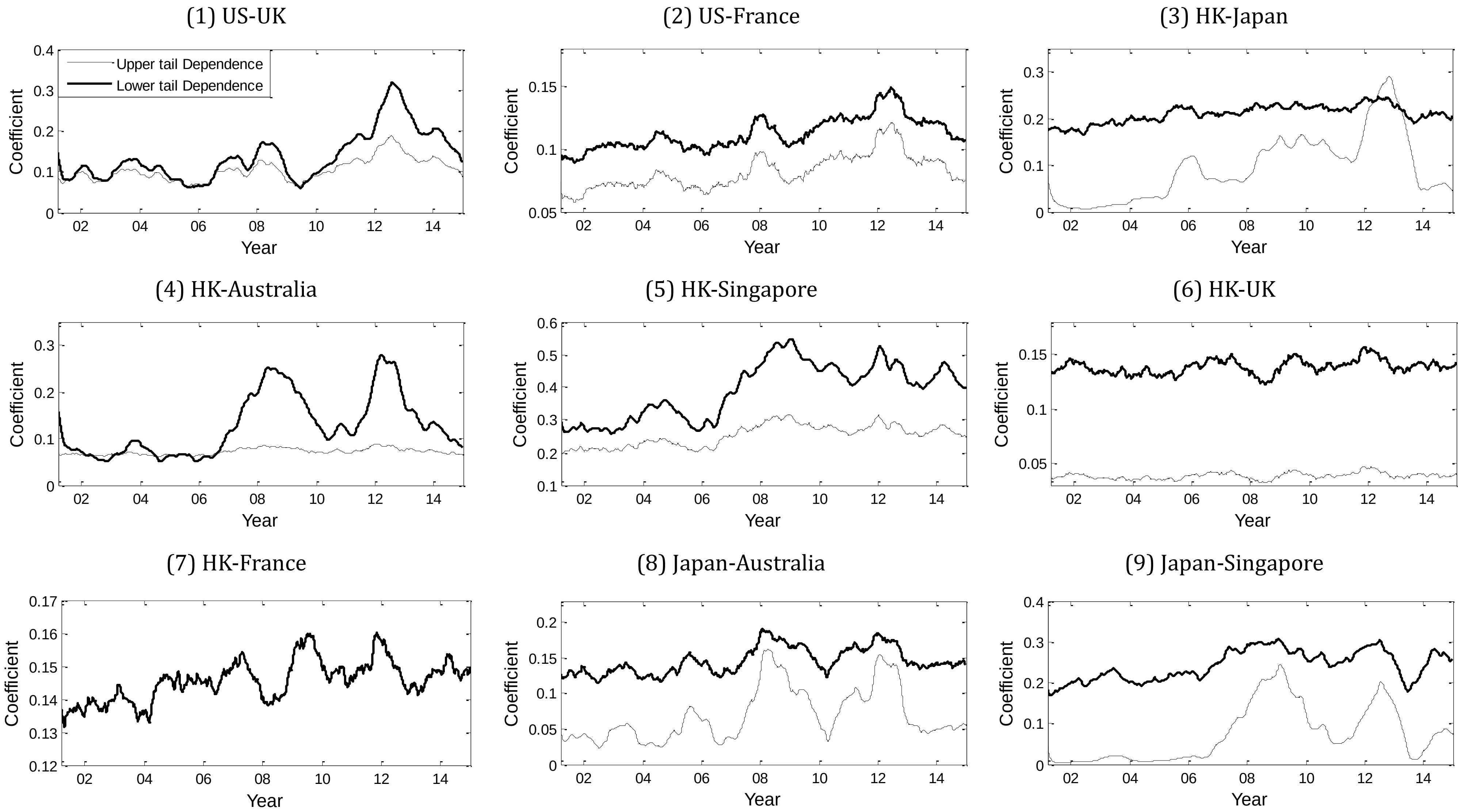

Figure 2 Time-varying tail dependences in Global RE markets

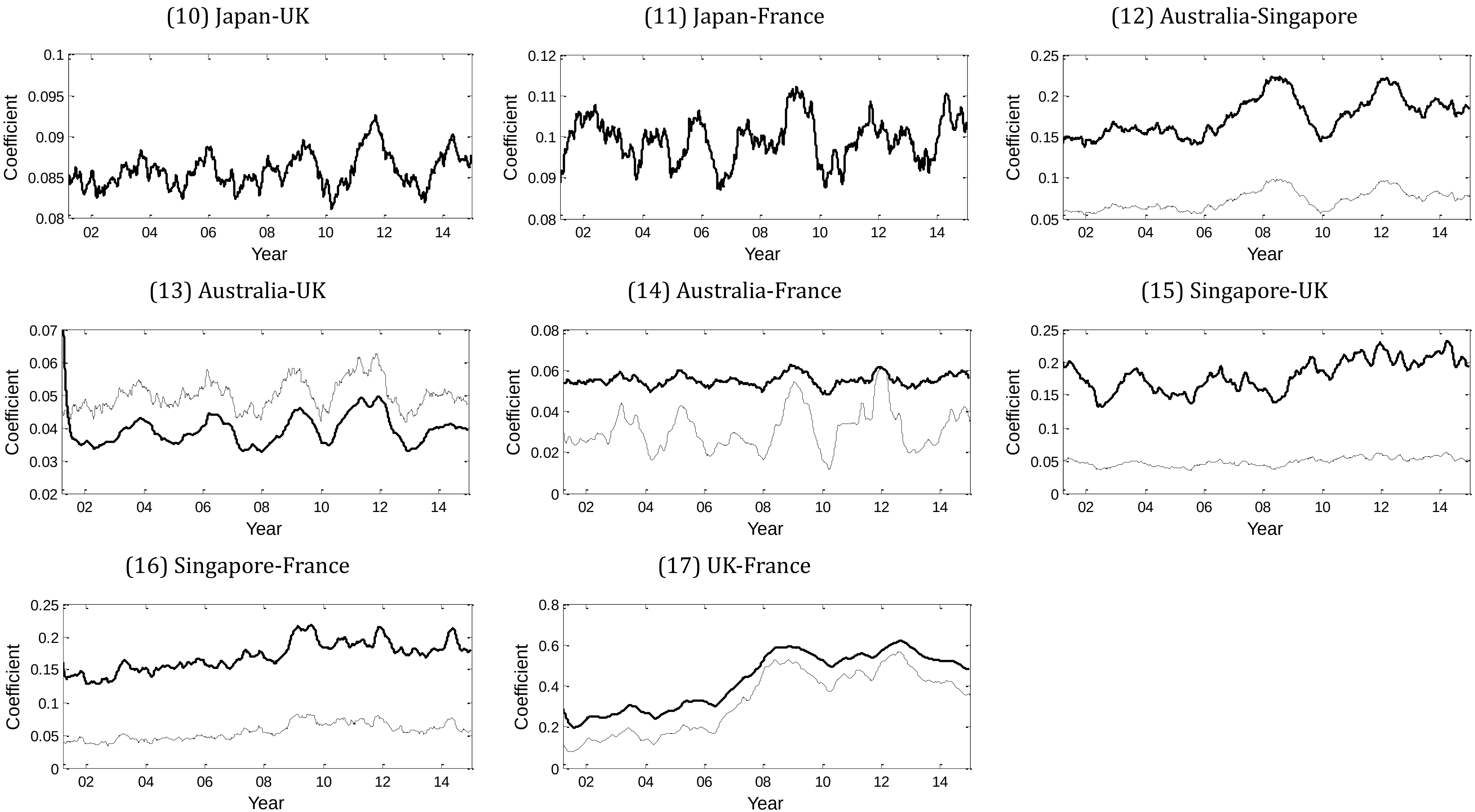

Figure2 Time-varying tail dependences in Global RE markets (Cont'd)