CHAPTER 4

The Volatility Spillover Effects Among Six Major Asian Sovereign Cds Markets

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1. Introduction

In a credit default swap (CDS), the seller of the CDS provides guarantees to the buyer's default risk in exchange for a recurring premium. Credit default swaps can be viewed as a protection against the potential occurrence of a default. Buyers of credit protection benefit from a reduction in credit concentration and regulatory capital, while sellers of credit protection can make money by inheriting substantial risk over a specific term without having to fund the position. The maturity of this relatively young class of assets ranges from 6 months to 30 years. 5-year maturity CDSs are the most liquid and widely traded in contrast to other maturities (Zhang, 2013). The CDS market is divided into two main sub-sectors: the corporate sector and the sovereign sector.

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The share of sovereign entities, which had less than 5% before the global financial crisis, in the overall market continued to rise and reached around 16% at the end of 2017 due to the impact of the global financial crisis and the European debt crisis (Ehlers, 2018). The size of sovereign CDSs reached its maximum (nearly 3 trillion dollars) in 2013, but it then decreased to 1.5 trillion dollars as of 2017.

The global economy has experienced systemic turbulence and heightened uncertainty during the past fifteen years. After the global financial crisis of 2007, which originated in the US subprime market and spread all over the world market quickly, investigating the spillover among financial markets across different entities (i.e., financial markets, countries, assets) has become prominent among academic studies. It has been observed that the interconnectivity of markets and economies contributes to spillover effects, resulting in higher systemic risk (Le et al., 2022). This is important not only for emerging markets but also for advanced markets. Although a financial system is resilient, it can become exceedingly fragile when there is a high level of connectivity because such connections might serve as shock amplifiers rather than shock absorbers (Giansante, 2010). The sovereign CDS market is characterized by a high degree of commonality between countries. This commonality would be significant source of risk among countries due to its highly contagion characteristics (Badaoui et al., 2013).

Several studies, such as Bostanci and Yilmaz (2020), Fender et al. (2012), and Yang et al. (2018), have shown that the dynamics of sovereign CDS are impacted by several external and internal factors in the economy. Several studies, on the other hand (e.g., Atil et al., 2016; Mili, 2018), have focused on the systemic risk posed by the joint movement of sovereign CDS. Spillovers across CDS markets raise the risk of CDS portfolios, and the risk increase when there is a significant degree of spatial interconnection between sovereign markets (Mili, 2018). Hence, keeping systemic risks under control is crucial for reducing the spread of risks.

This paper examines the volatility spillover indexes among the credit default swaps of six major Asian countries (China, Indonesia, Korea, Malaysia, Thailand, and Vietnam) from June 2008 to August 2022. Understanding the risk spillovers across associated sovereign credit default swaps is a key contribution of our work to the relevant finance literature. Wu et al. (2016) reach the conclusion that sovereign credit risk spreads quickly within regions before accumulating worldwide via prolonged risk spillovers. This study primarily aims to achieve the following two objectives: Our primary objective is to determine the direction of risk transmission in Asian markets. This enables investors who intend to guarantee the debts of Asian nations to anticipate future risks emanating from nearby countries in this market. Second, we intend to provide time-varying dynamics of total spillover indexes to capture critical insights into the dynamics of systemic risk in Asian credit markets. Since these countries are close to each other through trade and capital flows, figuring out the systemic risk gives various market actors such as buyer and sellers credit protections, regulators, and policymakers important information. Trade and capital flows are two significant factors of pairwise connectedness across countries (Bostanci and Yilmaz, 2020).

To address these issues, we estimate the volatility spillover indexes among 5-year maturity CDSs of six major Asian countries by using the Diebold and Yilmaz spillover index (DY index) proposed by Diebold and Yilmaz (2009, 2012). The empirical findings can be briefly summarized as follows: First, we find that China, Indonesia, and Vietnam are net receivers of the spillovers, whereas South Korea, Malaysia, and Thailand are net transmitters of volatility in the Asian CDS market. Second, the total volatility spillover index is around 79%, suggesting a very high level of connectedness among these Asian CDS markets and implying high systemic risk among markets. Third, our empirical finding provides strong evidence that the total spillover index can be used as an early warning of the rise of uncertainty in South Korea and China, especially during crisis periods. Last but not least, the existence of volatility transmission between CDS markets illustrates that an increase in volatility in one credit swap market is a clear indicator of a rise in volatility in other sovereign CDS markets.

The remaining sections of the paper are structured as follows. Section 2 provides the systematic literature review about credit default swaps. Section 3 describes the econometric methodology for generating the DY spillover index. Section 4 describes the data and provides descriptive statistics. Section 5 analyzes and draws conclusions from the empirical results.

2. Literature review

Though the literature on the determinants of CDS spreads is well-established, the study on information spillovers within CDS markets is sparse (Kim et al., 2015). Moreover, spillover analyzes of stock market and foreign exchange rate markets are common in the literature, but there are few studies on sovereign CDS market (Feng et al., 2022). After the European debt crisis, the spillover effect among sovereign CDSs started to attract the attention of researchers (Sun et al., 2020). The relationship between CDS premiums and other assets such as bond markets, stock markets, and exchange rate markets has been extensively studied in the literature. For example, Anton and Nucu (2020) examine the association between sovereign CDS and stock markets in nine Central and Eastern European (CEE) emerging economies using daily data from January 2008 to April 2018. They find evidence to support the existence of bidirectional feedback between sovereign CDS and stock markets in CEE countries.

Aktug et al. (2012), on the other side, investigate the dynamic interaction between sovereign CDS and bond markets in 30 emerging markets over the period from 2001 to 2007. Their empirical findings indicate that bond markets play a substantial role in the CDS price discovery process. Eyssell et al. (2013)

explore the determinants of levels and variations in sovereign CDS spreads in the Chinese market between January 2001 and December 2010. Using both country-specific and global factors, they conclude that China's internal economic conditions were more significant in explaining CDS spread levels and variations in earlier periods. During the global crisis, however, the significance of global variables comes to the fore. Furthermore, Yang et al. (2018) investigate whether interest rate and/or exchange rate have a substantial role in explaining sovereign CDS spreads. They find that the exchange rate has the greatest impact on sovereign CDS spreads, whereas domestic interest rates have a minor impact.

Our study is related to the large body of research that shows the interactions of emerging market sovereign credit default swaps. For instance, Wang and Moore (2012) use dynamic conditional correlation from the multivariate GARCH model to examine the integration of the CDS markets of 38 advanced and emerging economies with the US market during the subprime crisis. Empirical findings show that the Lehman shock appears to have increased the integration of developed markets. Moreover, De Boyrie and Pavlova (2016) utilized a wide range of sovereign credit default swap spreads of contracts with five years to maturity and investigated volatility spillovers among them. The countries included in the study include BRICS countries (Brazil, Russia, India, China, and South Africa) and MIST countries (Mexico, Indonesia, South Korea, and Turkey). However, CDS data of developed countries along with many financial indicators were used as control variables. According to their findings, Brazil and Mexico are two countries that dominate the volatility spillover effects, while China and South Korea have a net directional spillover from the other countries.

The DY spillover index can also be used in network analysis. For example, Bostanci and Yilmaz (2020) can be given as an example of this. Their empirical findings indicate that the high level of credit risk interconnectedness among sovereign CDSs is equivalent to that of stock markets and foreign exchange markets. Using the same methods as Bostanci and Yilmaz (2020), Sun et al. (2020) focus on three typical multi-country markets, i.e., the sovereign credit default swap, foreign exchange, and stock markets. Using data from 21 countries, they conclude that market sentiment causes many cross-border spillovers in the stock and sovereign CDS markets, whereas economic fundamentals and monetary policy drive such spillovers in the foreign exchange market. Kang et al. (2016) examine the dynamics of return and volatility spillover effects across five Asian sovereign credit default swaps (CDS), specifically China, Indonesia, Korea, Malaysia, and Thailand. They find that the Korean sovereign CDS is a transmitter of spillovers to other sovereign CDSs, whereas the Chinese sovereign CDS is a receiver of spillovers from other sovereign CDSs. Second, their empirical findings provide evidence that the total return and volatility spillover indices rapidly exploded during the subprime mortgage crisis of 2007 and the Lehman Brothers collapse of September 2008. In this study, we extended their study to add Vietnam into the five Asian countries and analysis period including the COVID-19 outbreaks.

As for the studies dealing with Asian markets, Guo et al. (2020) examine the lead-lag relationships between changes in Asian sovereign CDS spreads using the data of ten major Asian economies (China, Indonesia, Japan, Malaysia, Pakistan, Philippines, South Korea, Thailand, Kazakhstan, and Hong Kong). Their results show that changes in Kazakhstan's sovereign CDS spreads can be used to predict changes in the CDS spreads of other Asian economies. Zha et al. (2020) use sovereign and firm-level CDS data for China, Japan, and South Korea and examine the cross-country credit risk spillover by utilizing a bivariate GARCH-full-BEKK model over the period 2009–2018. They provide empirical evidence to support the strong credit risk interdependence valid among corresponding East Asian countries. We also extend such studies that examine the interrelationship of sovereign credit risk during the Global Financial Crisis and European Debt Crisis by using sovereign CDS: The relationship of sovereign CDS between advanced economies (Alter and Schüler, 2012; Atil et al., 2016; Bekiros et al., 2020; Blasques et al., 2016; Broto and Pérez-Quirós, 2014; Sabkha et al., 2019; Singh et al., 2021) and emerging markets (Beirne and Fratzscher, 2013; Daehler et al., 2021; Sabkha et al., 2019; Sensoy et al., 2017; Wang and Moore, 2012).

3. Methodology

We use the Diebold and Yilmaz (DY) spillover index through variance decomposition of the prediction error based on Diebold and Yilmaz (2009, 2012). In their first study, Diebold and Yilmaz (2009) employed Cholesky decomposition to decompose variance, but this approach suffers from the variable ordering problem. To address this issue, Diebold and Yilmaz (2012) adopted a generalized forecast error variance decomposition (GFEVD) using the approach of Koop et al. (1996) and Pesaran and Shin (1998), hereafter KPSS. In this study, we prefer to use the subsequent approach to avoid the variable ordering problem. A N-dimensional covariance stationary VAR (p) process can be defined:

$$x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \cdots + \Phi_p x_{t-p} + \varepsilon_t \qquad (1)$$

where x_t is continuous collection from $x_{1,t}, \ldots, x_{N,t}$, φ is a *NxN* coefficient matrix, and $\varepsilon_t \sim iid(0, \Sigma)$ is the vector of independently and identically distributed disturbances. The moving average (MA) representation of covariance stationary VAR process can be expressed as

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \qquad (2)$$

where A_i is the *NxN* coefficient matrices and can be obtained recursively as $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$. In this recursive formula A_0 enters the equation as a *NxN* identity matrix. By utilizing MA representation of reduced VAR model, we can calculate the forecast error variance decompositions of each variable to assess the portion of the *H*-step-ahead forecast error variance in forecasting x_i for each i= 1, 2,..., *N*. Hence, we can obtain the *H*-step ahead GFEVDs as follows:

$$\theta_{ij}(H) = \frac{r_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)^2} \tag{3}$$

where Σ represents the variance matrix of errors vector, ε, r_{jj} denotes the standard deviation of ε for the j^{th} equation, and e_i is the selection vector, which takes the value of one on the i^{th} element and zero otherwise. Since the sum of the rows of the variance decomposition matrix is not equal to one (i.e., $\sum_{j=1}^{N} \theta_{ij}(H) \neq 1$), it should be required to normalize each entry of the relevant matrix as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{4}$$

As a result of this calculation, we achieve to equalize the sum of variance decomposition including own shocks is one, that is, $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$. For all N numbers of variables, the sum of the total decomposition is equal to $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$. After obtaining the KPPS variance decomposition matrix, numerous relevant metrics may be calculated. The total spillover index is the first measurement, and it calculates the average contribution of spillover shocks across corresponding markets to the total forecast error variance. It can be computed as the following formula:

$$S(H) = 100\ x\ \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}(H) \tag{5}$$

In the second step, we can also calculate the directional spillovers sourced by all other markets *j* to market *i*:

$$S_{N,i\leftarrow .}(H) = 100\ x\ \frac{1}{N}\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}(H) \tag{6}$$

Likewise, the directional spillovers transmitted by the market asset *i* to all other market assets *j* can be calculated by using following formula:

$$S_{N,i\rightarrow .}(H) = 100\ x\ \frac{1}{N}\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ji}(H) \tag{7}$$

Finally, one may be interested in calculating the net spillovers of any market. This gives us valuable information about whether this market is a net risk transmitter or a net risk receiver in the whole market generated by all the markets used in the study. The formula below illustrates how we compute the net spillover effect.

$$S_{N,i}(H) = S_{N,i\rightarrow .}(H) - S_{N,i\leftarrow .}(H) \tag{8}$$

4. Data and descriptive statistics

We use monthly volatility frequency data in this study. The data includes six major Asian sovereign credit default swaps. The countries consist of China, Indonesia, Korea, Malaysia, Thailand, and Vietnam. We use the 5-year maturity credit default swap series for all countries. The CDS series of Asian countries has different observation lengths, and we dropped the excess observations of the long series to obtain the same number of observations. Our monthly volatility data spans from January 2008 to August 2022. All the data is obtained from the Thomson Reuters Eikon Database.

In this study, we use the first logarithmic differences of the daily CDS series as $r_t = log\left(\frac{P_t}{P_{t-1}}\right)\cdot 100$ when calculating the daily return series. P_t is the level of the CDS series in the period t. After calculating the daily return series, we derive the monthly realized volatility (historical volatility) series by using the approach of Barndorff-Nielsen and Shephard (2002) across six 5-year maturity CDS markets in Asia. The following illustrates the three-step monthly volatility calculation method: (1) Calculating the daily log returns for month t using the formula $r_{s,t} = log(\frac{P_{s,t}}{P_{s,t-1}})$, where $s = 1,2, \ldots. S$ represents the day of the month t, (2) Calculating the realized variance by adding the previous T squared returns: $RVar_t = \sum_{s=1}^{S} r_{t,s}^2$, and (3) Calculating the realized variance by taking the square root of the realized variance: $RVol_t = \sqrt{RVar_t}$. As a result of all these calculations, we obtain 171 observations for each sovereign CDS in Asia.

Table 1 reports some basic descriptive statistics of such a related monthly realized volatility series. The country with the lowest average volatility is Vietnam, while the highest average volatility is seen in China and Malaysia. Moreover, the South Korean sovereign CDS series has the largest standard deviation among others. The most important information about whether the observations converge to a normal distribution is understood by looking at the skewness and kurtosis values of the series. According to these statistical results, we can say that none of the CDS volatility series has a standard normal distribution. All CDS series have a positively skewed (or right-skewed) distribution. Besides basic descriptive statistics, we also provide the augmented Dickey-Fuller (1979) test statistic, which is commonly used to test whether a given time series is stationary or not. The results of the ADF test indicate that all the volatility of the CDS series is stationary at the 1% significance level.

Table 1. Descriptive statistics

	Mean	Median	Max	Min	Std. dev	Skewness	Kurtosis	ADF
China	0.15	0.13	0.69	0.03	0.08	2.73	13.16	-8.69***
Indonesia	0.14	0.12	0.76	0.03	0.09	3.49	18.21	-8.26***
Korea	0.14	0.12	0.93	0.02	0.10	3.90	25.92	-8.55***
Malaysia	0.14	0.13	0.71	0.03	0.09	3.24	16.26	-8.01***
Thailand	0.12	0.10	0.73	0.02	0.08	3.23	17.10	-8.01***
Vietnam	0.09	0.07	0.74	0.01	0.08	4.65	32.75	-4.75***

Table 2 shows the correlation table of the corresponding volatility series. The results of the correlation table indicate the existence of highly positive relationships between the corresponding volatility series. Given the high trade volume, high capital flows, and tight political relations between the countries under consideration, it is normally expected to see such a high correlation result. Furthermore, the highest correlation coefficient (0.93) is between Indonesia and Malaysia, while the lowest coefficient (0.79) is between Vietnam and China. Since the standard correlation table cannot capture the lag-lead relationship, we need spillover effect analysis to capture the dynamic mechanisms within such sovereign credit markets.

Table.2 Correlation table

	China	Indonesia	Korea	Malaysia	Thailand	Vietnam
China		0.89	0.88	0.91	0.86	0.79
Indonesia	0.89		0.89	0.93	0.89	0.87
Korea	0.88	0.89		0.91	0.91	0.86
Malaysia	0.91	0.93	0.91		0.91	0.85
Thailand	0.86	0.89	0.91	0.91		0.84
Vietnam	0.79	0.87	0.86	0.85	0.84	

Figure 1 shows the series of realized volatility in six Asian CDS markets from July 2008 to August 2022. First, the values of all CDS volatility series reached their maximum in the 2008 GFC during the observation period. Second, the next highest point is observed during the most recent health crisis, the COVID-19 pandemic. Apart from these, it is interesting to note that the CDS volatility series moves in sync during the observation period. These co-movements of the volatility series can be seen easily from the previous correlation table. As stated by Badaoui et al. (2013), the Asian sovereign CDS markets show very tight relationships among themselves, and this commonality would be a considerable source of risk for countries due to its highly contagious nature. In the next section, we will put forth some empirical results that we use to test the validity of this argument.

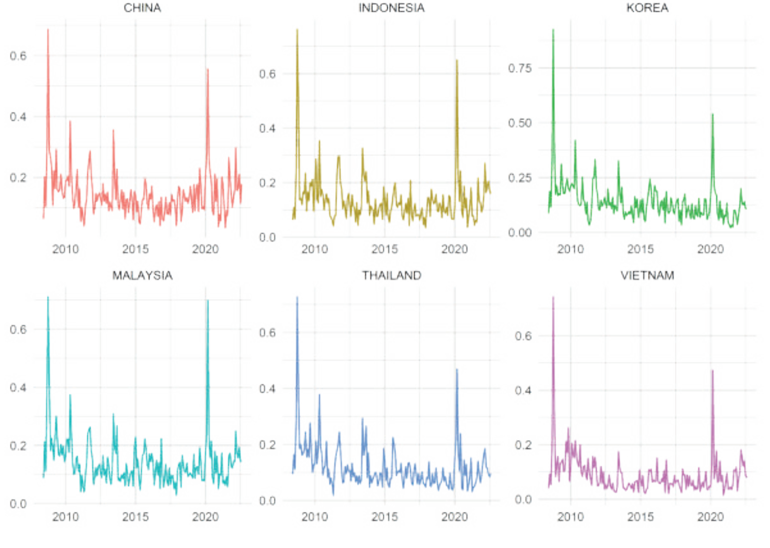

Figure 1 The volatility of return CDS series for six Asian countries

5. Empirical results and discussions

We use the generalized FEVD framework by Diebold and Yilmaz (2012) to figure out the total, directional, and net (pairwise) spillovers. The optimal lag length for our VAR model is determined by the Akaike Information Criterion (AIC). The estimation of full sample volatility spillover results and their decomposition as transmitters and receivers for six major Asian sovereign credit default swaps are provided in Table 3. In addition, we calculate the net directional spillover indexes from these transmitters and receivers for every sovereign CDS volatility series. The variable in the row denotes the volatility spillover contributions from one variable to other variables, whereas the variable in the column represents the spillover recipients from other variables. Both calculations located at the ends of rows and columns include variables' own spillover effects. Therefore, the so-called "*to others*" column in the table represents the effect of a sovereign CDS on another sovereign CDSs. Likewise, the values in the column under '*from others*' illustrate the volatility spillover impact of other sovereign assets. The sum of the values in the rows and columns indicates the total volatility spillovers to (received by) and from (transmitted by) each variable, excluding the own-variable volatility spillovers. In addition, the net spillover effect is determined by subtracting "*to others*" from "*from others*". This estimation is crucial for determining whether an asset is a net transmitter or net receiver on the market. The total volatility spillover index can be obtained by dividing either the row sum (to others) or column sum (from others) to the number of variables (six for our study).

Table 3 presents the volatility spillover estimation results for six major Asian economies. Our empirical findings are as follows: First, the volatility spillover indexes among these countries are relatively high due to their highly interconnected economies. We see this strong relationship from correlation analysis (see Table 2) as well. Unlike correlation analysis, volatility spillover analysis gives us information about the direction of risk among sovereign credit default swaps. Second, it is worth noting that although China has the largest economy among these Asian countries, it is observed that it has less impact on the transfer of financial risk than the others. It can be explained by the market situation of Asian derivatives. Hohensee and Lee (2006) find that there exists a strong inverse relationship between market sophistication and regulatory restrictions. According to DB Global Markets Research (see Hohensee and Lee, 2006), Philippines, Korea, Malaysia, and Thailand have the most liquid sovereign credit default swap market, while China has the least liquid credit default swap market among other emerging markets. Given that an active credit derivatives market may enhance the safety and efficiency of the financial system through its pricing and diversification of credit risk, active markets are expected to be less affected by market risk. To see if this is the case, we just need to focus on the last column in Table 3, called "*from others*". This argument is fully supported by our findings, as shown in Table 3. Third, China, Indonesia, and Vietnam are the risk-taking countries, whereas South Korea, Malaysia, and Thailand are the risk-contributing countries. Finally, our empirical result shows that the total volatility spillover index is 79%, illustrating serious risk spillover among the Asian CDS derivative markets.

Table 3. Volatility spillover table

	From (*j*)						
To (*i*)	China	Indonesia	South Korea	Malaysia	Thailand	Vietnam	**From others**
China	20.98	15.98	16.55	18.18	16.57	11.73	79.02
Indonesia	15.7	19.37	16.26	17.82	17	13.85	80.63
Korea	15.81	14.75	20.91	17.74	17.51	13.29	79.09
Malaysia	16.18	16.03	16.36	20.92	17.41	13.11	79.08
Thailand	15.02	14.98	16.78	17.87	22.29	13.06	77.71
Vietnam	13.65	15.36	16.58	16.52	16.3	21.59	78.41
To others	76.35	77.1	82.53	88.13	84.78	65.05	473.94
Directional including own	97.33	96.48	103.44	109.05	107.07	86.64	Spillover index
NET spillovers	-2.67	-3.52	3.44	9.05	7.07	-13.36	78.99 %

In the previous analysis, we make a very strong assumption that the spillover effects among CDS markets do not change over time. This assumption is inconsistent with the reality of financial markets. Even daily events cause the nexus between financial markets to change. Therefore, it may lead us to make mistakes while making political inferences with the empirical results obtained from the full sample VAR model. For example, all economies have been seriously affected by the COVID-19 outbreak. It would be a very naive approach to say that the risks carried and conveyed by the CSD markets in the pre- and post-COVID-19 period remain the same and to comment accordingly. To address this issue, we estimate the VAR model using 40-month rolling windows and evaluate the total time-varying dynamics of the volatility spillover index. Besides, we set a forecast horizon of H = 12. Figure 2 reports the time-varying total volatility spillover index among the six major Asian sovereign CDS markets. The empirical result shows us that the total volatility spillover index is not constant and fluctuates over time. As discussed by Balcilar et al. (2018, 2020), our empirical findings reveal that the total risk spillover among financial markets tends to increase during important economic events such as economic crises, wars, health crises, droughts, etc. Moreover, He et al. (2019) propose that one can use the total spillover index as an early warning for a systemic risk. Sovereign CDSs show the debt burden of countries. Accordingly, this finding shows us that the government borrowing risks of these countries are seriously interconnected with each other. In other words, the increase in the total spillover index exposes these six countries to a similar interest rate risk.

Figure 2 also reports the monthly economic policy uncertainty indexes for South Korea and China[2] that are used in this study. It would be reasonable to plot such economic uncertainty indexes (shown on the left-hand side y-axis) alongside our time-varying total volatility spillover index (shown on the right-hand side y-axis) to see if the total volatility spillover index is an early warning for systemic risk in Asian markets. As we see in the figure, the total volatility spillover index in the Asian CDS market moves in parallel to economic policy uncertainty indexes in some periods when the structural breaks occur. For example, the total spillover index and Korean economic policy uncertainty fell sharply at the beginning of 2012. On the other hand, the economic policy uncertainty indexes of these two countries started to decrease after mid-2016, and our spillover index can be seen as an early warning of this economic recovery. Lastly, the figure illustrates that the total spillover index rises sharply after COVID-19 outbreaks, similar to the movement

2 Due to the availability of data, we illustrate just these two countries' economic policy uncertainty indexes. We obtain the related data from the website at https://www.policyuncertainty.com/index.html.

of economic policy uncertainty indexes[3]. The COVID-19 has caused a catastrophic lockdown that has triggered a global recession and destabilized global financial markets (Abuzayed et al., 2021). The total volatility spillover index reaches its maximum point at the beginning of the COVID-19 pandemic, and it slowly decreases then. The fact that this value remains so high shows us that the overall risk of CDS caused by COVID-19 is still high.

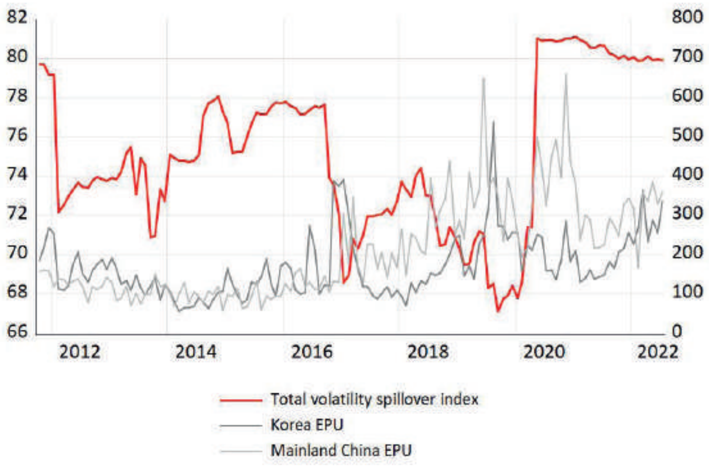

Figure 2. Total volatility spillover index vs economic policy uncertainty

6. Conclusion

This paper builds upon the existing literature on volatility spillovers across financial markets and examines the degree of connectedness across six major Asian CDS markets (China,

3 Of course, we cannot expect these indexes to move in parallel because the EPU indexes for China and South Korea are calculated by considering newspaper articles that contain at least one term in each of three term sets: economics, policy, and uncertainty. On the other hand, the total spillover index is obtained from the variance decomposition analysis of standard VAR model.

Indonesia, Korea, Malaysia, Thailand, and Vietnam) using data from January 2008 to August 2022. We estimate the various volatility spillover indexes by using the spillover index developed by Diebold and Yilmaz (2009, 2012) based on the forecast error variance decomposition. The main results are the following: The full estimation results indicate that the total volatility spillover index is around 79%, suggesting a very high level of connectivity among these Asian CDS markets and implying high systemic risk among markets. The directional risk spillover index results provide evidence that the direction and degree of risk spillovers among these Asian markets differ. Among them, Malaysia (Vietnam) contributed most (least) to the total volatility in the system during the analyzed period. Moreover, the results also suggest that China, Indonesia, and Vietnam are net receivers of the spillovers, while South Korea, Malaysia, and Thailand are net transmitters of volatility in the Asian derivative market. We also carry out a time-varying analysis to detect whether the total spillover index is stable over time. The results suggest, first, that the total spillover index rises sharply during important economic events such as the recent COVID-19 pandemic. Second, this spillover can be used as an early warning of economic uncertainty in some Asian markets. Third, volatility transmission exists between various financial markets, meaning that an increase in volatility in one credit swap market is a clear indicator of a rise in volatility in other sovereign CDS markets. Our findings will certainly be of interest to buyers' and sellers' credit protection, regulators, and policymakers who need to understand the mechanisms of cross-market credit risk transmission among Asian sovereign CDS markets. They should pay close attention in particular to the volatility spillover impact and the volatility of the sovereign CDS markets. This paper suggests further research into sovereign CDS indexes in various global regions.

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