THE RIMINI CENTRE FOR ECONOMIC ANALYSIS

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Min Zhang
Nanjing University, China

Adam W. Kolkiewicz
University of Waterloo, Canada

Tony S. Wirjanto
University of Waterloo, Canada
The Rimini Centre for Economic Analysis (RCEA), Italy

Xindan Li
Nanjing University, China

THE IMPACTS OF FINANCIAL CRISIS ON SOVEREIGN CREDIT RISK ANALYSIS IN ASIA AND EUROPE

The Impacts of Financial Crisis on Sovereign Credit
Risk Analysis in Asia and Europe

Min Zhang[a], Adam W. Kolkiewicz[b], Tony S. Wirjanto[c], and Xindan Li[a]

a. School of Management and Engineering, Nanjing University.

b. Department of Statistics & Actuarial Science, University of Waterloo.

c. (Corresponding Author) Department of Statistics & Actuarial Science, and

School of Accounting & Finance, University of Waterloo.

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Abstract. We investigate the nature of sovereign credit risk for selected Asian and European countries based on a set of sovereign CDS data over an eight-year period that includes the episode of the 2008-2009 global financial crisis. The principal component analysis results indicate that there exists strong commonality in sovereign credit risk among the countries studied in this paper following the crisis. In addition, the regression results show that commonality is importantly associated with both local and global financial and economic variables. There are also important differences in the sovereign of credit risk behavior between Asian and European countries. Specifically, we find that foreign reserve, global stock market, and volatility risk premium, affect Asian and European sovereign credit risks in the opposite direction. Lastly, we model the arrival rates of credit events as a square-root diffusion process from which a pricing model is constructed and estimated over pre and post-crisis periods. The resulting model is used to decompose credit spreads into risk premium and credit-event components. For most countries in our study, credit-event components weight more than risk-premiums, suggesting that, in the long term, investors are perhaps more concerned with the prospect of sovereign-specific credit events than systemic sovereign credit risks.

1 Introduction

Sovereign credit risk has emerged as an increasingly prominent research topic in Finance recently, thanks to the steady growth of sovereign credit default swap markets worldwide in terms of their size and volume, and to the important role of implied sovereign credit risk in global financial markets. Sovereign credit risk refers to the risk of a government failing to meet its loan obligations, or defaulting on loans it guarantees. As Longstaff et al. (2011) argued, a better understanding of the nature of the underlying sovereign credit risk will also help large financial institutions and other financial market participants to better diversify the risk of global debt portfolios, and better influence both the cost and flow of capital across countries.

At the same time, the emergence of the European sovereign-debt crisis in the aftermath of the 2008-2009 global financial crisis, highlighted by the collapse of Lehman Brothers in 2008, has also raised a widespread public concern. Some even argued that this Euro Crisis could inevitably lead to systemic sovereign credit risk. Under these circumstances, better understanding and careful analysis of the structure of sovereign credit spreads in Europe appear to be timely.

In this paper, we investigate the nature of sovereign credit risk in a few selected Asian and European countries by posing a number of research questions: (i) what factors determine and affect sovereign CDS spreads, and to what extent?, (ii) does sovereign credit risk in different regions of the world share certain common features?, and (iii) how can we price the sovereign credit risk?

We follow the study by Longstaff et al. (2011) very closely. In particular, we adopt the basic framework outlined in Longstaff et al. (2011). However, we depart from it in several important ways. First, Longstaff et al. (2011)'s study focuses on the sovereign CDS data of a large number of countries in Asia, Latin America, and Europe for the 2000-2010 sample period. In this paper, we focus our study on the sovereign credit spreads of a few selected emerging markets in East Asia and a few relatively large developed countries in Europe for the sample that spans over the period from September 2004 to August 2012. This sample choice allows us to conduct a comparative study of not only the sovereign CDS structure between the selected Asian and European countries, but more importantly, it also enables us to carry out a systematic investigation into the sovereign CDS structure in these countries in the pre and post-crisis periods.

Second and, as a result, this paper departs from the scope of the study in Longstaff et al. (2011) in performing Principle Component Analsysis (PCA) not only for the full sample, but also for two subsample periods corresponding to the pre and post-crisis episodes. In addition, as a minor technical modification, we also correct our t-

statistics not just for heteroskedasticity, but also for autocorrelation in the regression error terms, using the procedure advocated by Newey and West (1987) with data-determined lags. This, we argue, is at least an equally likely violation of the i.i.d assumption in the regression error terms in the context of our study. Our first two key findings can be summarized as follows. First, the regional factor has an important influence on the sovereign credit risks of a nation. This is highlighted by the opposite signs of the loadings for the second principal component (PC). Unlike the results reported in Longstaff et al. (2011), which point to an important association between sovereign credit risk and global factors only, our results indicate that both global and local factors play a vital role in determining the sovereign credit risks.

Third, this paper departs from Longstaff et al. (2011) in the choice of the pricing model. In particular, they assume that the default rate $\lambda^{\mathbb{Q}}$ follows a log-normal process, while we assume that the default rate is generated by a square-root model of Cox, Ingersoll and Ross (1985) - hereafter the CIR model. This pricing model is subsequently estimated by the method of maximum likelihood (ML) separately over two subsamples to account for potentially neglected but important structural changes in the sovereign credit risks in the selected countries in the pre and post-crisis periods.

The remaining parts of this paper are organized as follows. In Section 2, we introduce the data set used in this paper and provide rationale for the choice of the particular data set used in our study. In Section 3, we carry out a series of PCAs on the sovereign Credit default swaps (CDS) spreads of the selected countries to determine whether there is evidence of commonality of sovereign credit spreads among countries in our study. Given evidence of this, we proceed to perform a series of regression analyses to determine the sources of this commonality. The remaining sections of the paper propose a new pricing model, provide ML estimates (MLEs) of the parameters of the model over the full and sub-samples, and present a useful decomposition of the sovereign credit risk. Concluding remarks are provided in the last section.

2   The Data

This paper employs sovereign Credit Default Swaps (CDS) data for a few selected Asian and European countries for the following reasons. First, as mentioned earlier, the European sovereign-debt crisis in the aftermath of the 2008-2009 global financial crisis has raised a widespread public concern. Europe is important to the world economy, not only because it contributes nearly one fifth of the global GDP, but also because its economy grew faster than that of the U.S. before the crisis (Unit

and Britain, 2011). In addition to this, many U.S. companies rely on the European markets for a large part of their profits. Thus, for instance, when Greece requested a loan to repay its government debts in early 2010, the U.S. stock market took a big loss of nearly US$2.5 trillion. This, in turns, impacted the European debt market considerably. As a result, there was much anticipation among market watchers that the sovereign credit risk would eventually spike in the global financial system, as argued in Ang and Longstaff (2012). This concern was further exacerbated by the downgrading of a number of European countries, and the U.S, which are all considered to be world's leading financial institutions,[2] and by the ever widening credit spreads in all of these countries.

Against this background, we focus on relatively "large" countries in the European Union: France, Germany, Italy and Spain, in order to capture the features of the sovereign CDS spreads in Europe.

$Parameters$	$Values$
S_0	1
δ_0	0.02
$X_2(0)$	0.02

Table 1 shows the current Standard & Poor credit ratings for all of the sovereigns studied in this paper. First, as shown in the table, Germany maintains a triple A rating, which indicates a high degree of reliability and best credit quality. Germany is selected to be included in this study because it is the healthiest economy in Europe for the period under study. See e.g. (Unit and Britain, 2011). Next, France is selected to be included in our study for its relatively favorable economic condition. Although France was downgraded to AA+ in January of 2012 by Standard & Poor, it has still a relatively safe credit rating. In contrast, Italy and Spain are examples of sovereigns struggling through the debt crisis with huge deficits and facing difficulties to pay off their government debts.[3] Spain has a BBB- credit rating, which is only one rating away from a devastating level. Italy is slightly better than Spain with a BBB+ rating. It is important to note that all of these selected countries have

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[2]Standard & Poor's downgraded the credit ratings of the following countries and banks: Greece was downgraded to a junk status in April 2010; the U.S. Treasury was downgraded from AAA to AA+ in August 2011; Italy, Spain, Portugal, Cyprus were downgraded by two notches and France, Austria, Malta, Slovakia and Slovenia by one notch in January 2012; and three French banks, including BNP Paribas, were also downgraded in October 2012.

[3]Initially, we planned to include Greece in the list of our sovereigns. But Greece sovereign CDS spread was simply too large (and sometimes exceeded 100%) in the past two years to be included in our study

Table 1: Standard & Poor Credit Rating for Sovereigns[*]

Entity	Local Currency Rating	Foreign Currency Rating
China	AA-	AA-
France	AA+	AA+
Germany	AAA	AA
Italy	BBB+	BBB+
Japan	AA-	AA-
Korea	AA-	A+
Philippines	BB+	BB+
Spain	BBB-	BBB-

Note: Standard & Poor Rating Criteria: AAA: Best credit quality, extremely reliable; AA: Very good credit quality, very reliable; A: More susceptible to economic conditions, still good credit quality; BBB: Lowest rating in investment grade; BB: Caution is necessary, best sub-investment credit quality.
[*] Datasource: Standard & Poor Website, retrieved on Nov. 2012

relatively large economies: Germany is the fourth largest economy in the world and the largest in the European Union; France is the fifth largest economy in the world and the second largest in Europe; Italy is the eighth largest in the world and fourth largest in Europe; and Spain is the sixth largest in Europe. Generally speaking, large economies are more interesting to study as they are expected to exert larger influence over the world economy compared to smaller economies.

Second, since early 1990s, China's economy has started to take off, fueled by its efforts to transform a planned economy to a market oriented economy. Over time, it has become a new force to be reckoned with in the global economy. According to IMF (2012), as the second largest economy in the world, China has increasingly exerted its vital role in the world with its relatively high economy growth rates, high GDP and large purchasing power parity, increased exporter and importer capacity, and large foreign exchange reserves. However, despite the ongoing reforms, China's economy still exhibits a quite distinctive feature relative to the economies in the rest of the world, in terms of the tight control it exerts on its macroeconomic system and limited economic access. In particular, according to Zhu and Lague (2012), the state-owned enterprises currently still dominate much of the country's economy and exert considerable control over key industries and resources, such as energy, electric, steel, telecom, transportation, and finance, in China. These distinctive features make it interesting to study China's sovereign CDS spreads. The following research questions arise naturally with regard to China: (i) what factors determine China's sovereign CDS spreads, and to what extent?, (ii) do they share the same dependencies as those of the other major countries?, and (iii) can they be priced by using the same

methodology? If the answer is negative, what are the modifications of the pricing model needed for China? In addition to China, three other East-Asian countries: Japan, South Korea and the Philippines, are selected to be included in our study. With this selection, we hope to be able to analyze the degree and nature of sovereign CDS spread comovements in both the European and Asian continents, and examine whether there is any potential regional factors that influence these spreads. Japan is the third largest economy in the world, only after the U.S. and China, with the same AA- credit rating as China. South Korea is one of the more actively traded sovereign credit country in Asia and is one of the G-20 major economies. Lastly, the Philippines is a relatively small economy in Asia with a relative low credit rating.

Next, we discuss the Credit Default Swaps (CDS) data in more detail. CDS is a bilateral contract in which two counterparties exchange periodic premiums. It is typically expressed in basis points on the notional amount as a CDS spread, with a contingent payment made by the protection seller following a credit event of a reference security. The contingent payment is structured to offset the loss that a typical lender would incur upon a credit event. Although the credit event and the settlement mechanism are flexible and negotiated between the counterparties, most traded CDS follow a common specification proposed by the International Swaps and Derivatives Association (ISDA) (Schönbucher, 2003, and Bluhm et al., 2002).

To identify a CDS contract, the following pieces of information are usually required: reference obliger and investors' reference assets, definition of the credit event, notional amount of the CDS, start of the contract and start of the protection, maturity date, credit default swap spread, frequency and day count convention for the spread payments, and payment at the credit event and its settlement. The maturity time of CDS contracts may range from one to ten years, and usually the five years CDS is quoted as a benchmark. Similar to the common CDS contracts for corporate issuers, a standard CDS contract for a sovereign issuer allows the contract seller to earn a semi-annual premium, expressed in basis points as a CDS spread per notional amount, and protects the contract buyer with contingent payment when the credit event occurs. However, the definition of credit events for a sovereign CDS is distinct from that used for corporate issuers. Typically, in the case of a soveriegn issuer, the credit events include obligation acceleration, failure to pay, restructuring and repudiation/moratorium.[4] Besides, when physical delivery is needed for settlement, only bonds denominated in standard specified currencies[5] in external markets are

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[4]Note that default is not included in the credit event definition, since "there is no operable international bankruptcy court that applies to sovereign issuers," according to Pan and Singleton (2008).

[5]Standard specified currencies consist of any of the lawful currencies of Canada, Japan, Switzer-

deliverable. For sovereign issuers without such bonds, loans will be included in the set of deliverable assets.

As pointed out by Pan and Singleton (2008), currently in the global sovereign CDS markets, contracts with a five-year maturity apparently have the best liquidity, accounting for about 40% of the market volume. Three and ten-year contracts are also popular, which cover about 1/5 of the volume separately. In this paper, we focus on five-year sovereign CDS contracts of the eight countries from Asia and Europe for the past eight years spanning from September 2004 to August 2012. The covered time period is long enough to capture the movements of the CDS premiums before and after the episode of the global financial crisis. Data used in this paper are retrieved from the Bloomberg data base, which gathers CDS quotations from other industry sources. All of these CDS contracts are US dollar-denominated. In summary, our study utilizes five-year sovereign CDS spreads data from China, France, Germany, Italy, Japan, Korea, the Philippines, and Spain for a period that spans from September 2004 to August 2012. In addition, we also consider a liquidity factor in our study since according to Pan and Singleton (2008), the levels of CDS spreads can largely be attributed to credit assessments instead of illiquidity.

Figure 1 plots the daily sovereign CDS spreads for the selected Asian and European countries As shown in the figure, for each region, there appears to be visible patterns of strong commonality among the sovereign CDS spreads. Another noticeable feature in the figure is the distinct pattern of spread movements between countries in Asia and Europe. For the Asian region, the maximum and most volatile spreads occurred during the period from 2008 to 2009, and they recovered to some extent by late 2009. Then, in mid-2011, they experienced the second largest fluctuation. Conversely, sovereign CDS spreads for European countries remained at a relative low level before 2008. Since the 2008-2009 financial crisis, these spreads have started to increase gradually. They peaked in 2011 and 2012. The highest peak occurred in the past two years, which is much larger than the spreads around 2008. Thus, although both regions are affected by the financial crisis and the Euro Debt crisis, Asian countries are impacted to a larger degree during the crisis, while European countries have been influenced more substantively after the crisis. We also find that in Asia, the spreads in the Philippines is consistently ranked the highest, followed by Korea, China, and Japan, and the spreads in China and Japan are ranked quite close to each other. In Europe, Spain has the largest spreads followed by Italy, France and Germany.

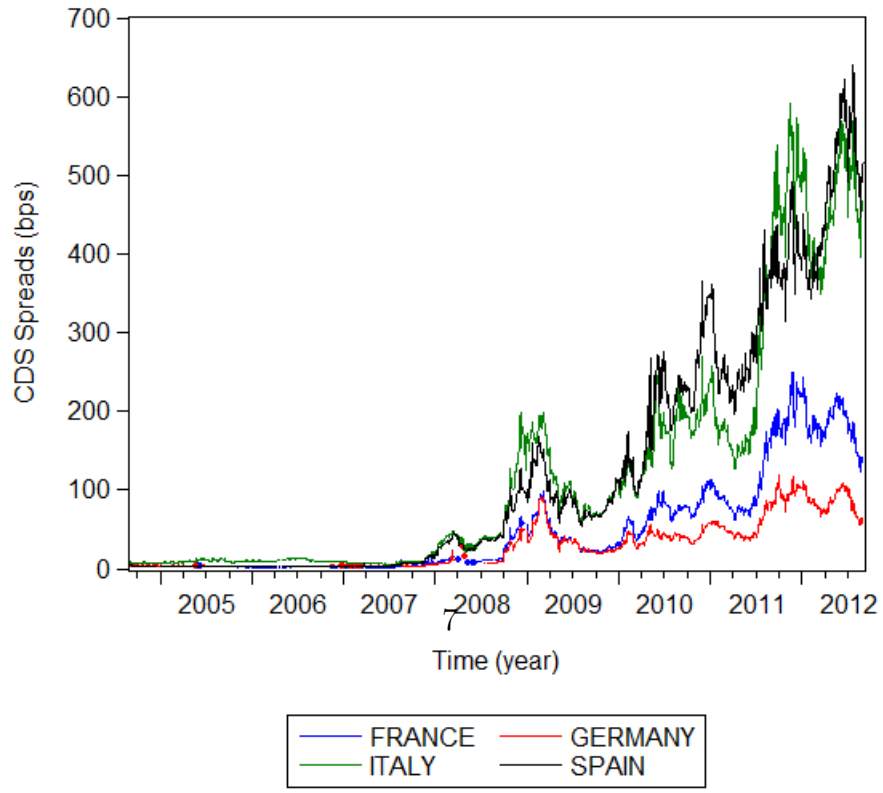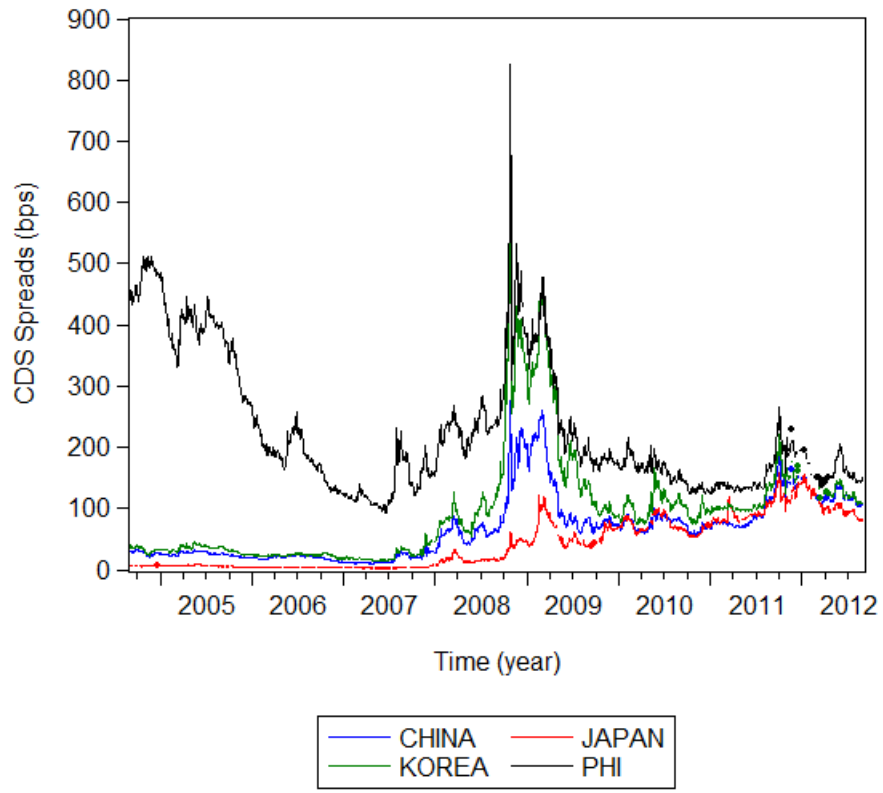land, the United Kingdom, the United States and the Euro, according to the ISDA.

Figure 1: Plots of Daily Sovereign CDS Spreads from Sept 2004 to Aug 2012

Table 2: Descriptive Statistics for Sovereign CDS Spreads[1]

| Entity	N	Range	Minimum	Maximum	Mean	Median	SD	a.c.[2]
China	2002	266.215	10.082	276.298	64.453	61.337	50.997	0.996
France	2025	248.125	1.5	249.625	49.951	21.485	63.268	0.998
Germany	1947	117.033	2.125	119.158	29.978	21.531	30.680	0.997
Italy	2055	585.961	5.575	591.536	122.993	47.833	153.330	0.997
Japan	1962	155.084	2.125	157.209	42.438	19.135	41.979	0.998
Korea	2000	661.125	13.75	647.875	94.034	82.399	90.112	0.995
Philippines	2009	731.561	93.214	824.775	229.481	187.130	111.231	0.995
Spain	2075	638.413	2.554	640.966	125.176	41.500	158.781	0.997

[1] Descriptive statistics for daily spreads for five-year sovereign CDS contracts from Sept 2004 to Aug 2012. Spreads are measured in basis points (0.01%).

[2] a.c. is the first-order sample autocorrelation coefficient.

Table 2 provides descriptive statistics for the daily sovereign credit spreads in the eight selected countries. As shown in the table, the range and mean of the CDS spreads vary considerably from country to country. Germany has the smallest mean at 29.978 basis points (bps), and the smallest range at 117.033 bps. This is followed by France, Japan and China with means around 50 bps and ranges less than 300 bps. Korea has an average spread less than 100 bps. Italy and Spain have similar means around 120 bps and similar ranges around 600 bps. Lastly, the Philippines has the largest range, minimum, maximum, mean and median spreads among all of the countries. This is in line with our earlier observation on the spread plots.

Table 2 also reports sample autocorrelation coefficients of the sovereign CDS spreads of each country for a first lag. As shown, all of spreads are highly persistent across time. For further analysis of this property, the sample autocorrelation and partial autocorrelation coefficients for the first fifty lags are calculated and plotted in Figure 2 and Figure 3 respectively with approximate 95% confidence intervals. The significant sample autocorrelation coefficients of the CDS spreads, which tail off gradually with the lags, are visible in Figure 2; while in Figure 3, the sample partial autocorrelation coefficients are all cut off after lag 1, with small coefficients oscillating between positive and negative numbers and occasionally being statistically significant at the 5% level. Overall, the evidence seems to confirm the earlier conclusion that the sovereign CDS spreads are highly autocorrelated across time. In addition, we also conduct a goodness-of-fit test on the first-difference of the CDS spreads for each country. Figure 4 shows the Q-Q plots of these first-differences against the referenced normal distribution for the selected countries. The Q-Q plots indicate that none of them appears to have been generated by a normal distribution.
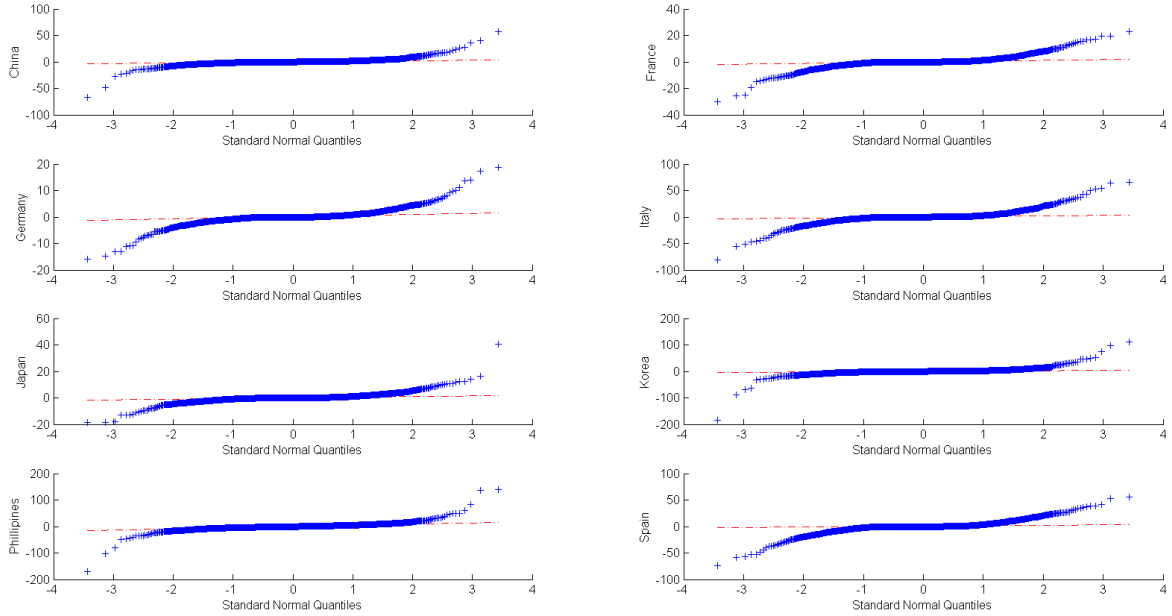
Comparing Table 1 with Table 2, we can draw a conclusion that the range, mean,
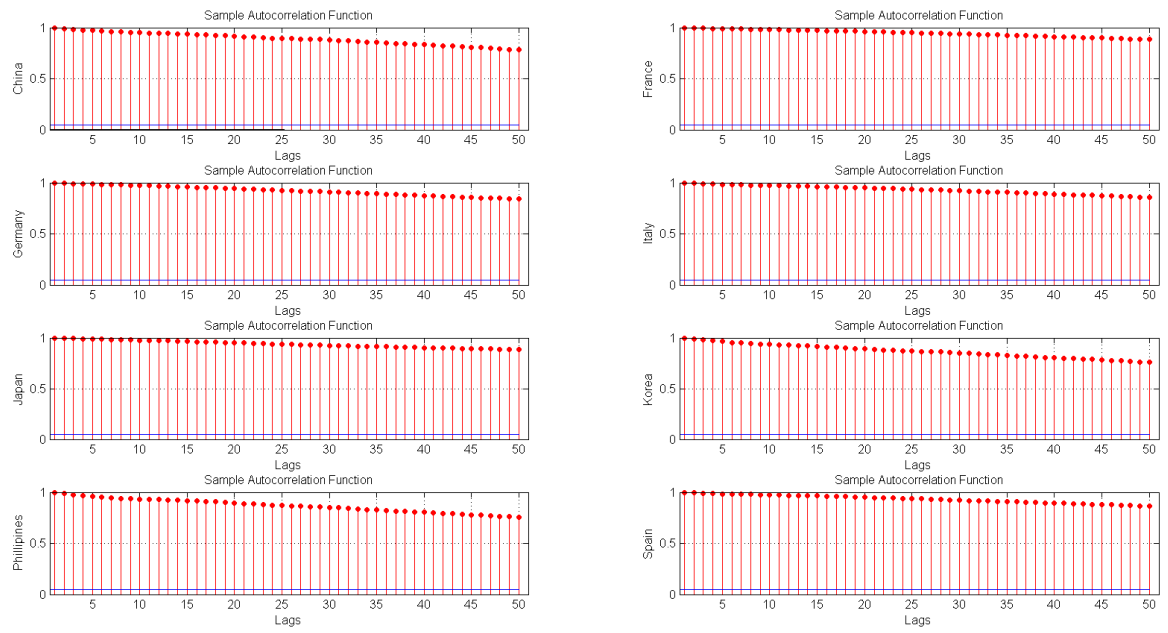
Figure 2: Sample Autocorrelations of Daily Sovereign CDS Spreads from Lag 1 to Lag 50

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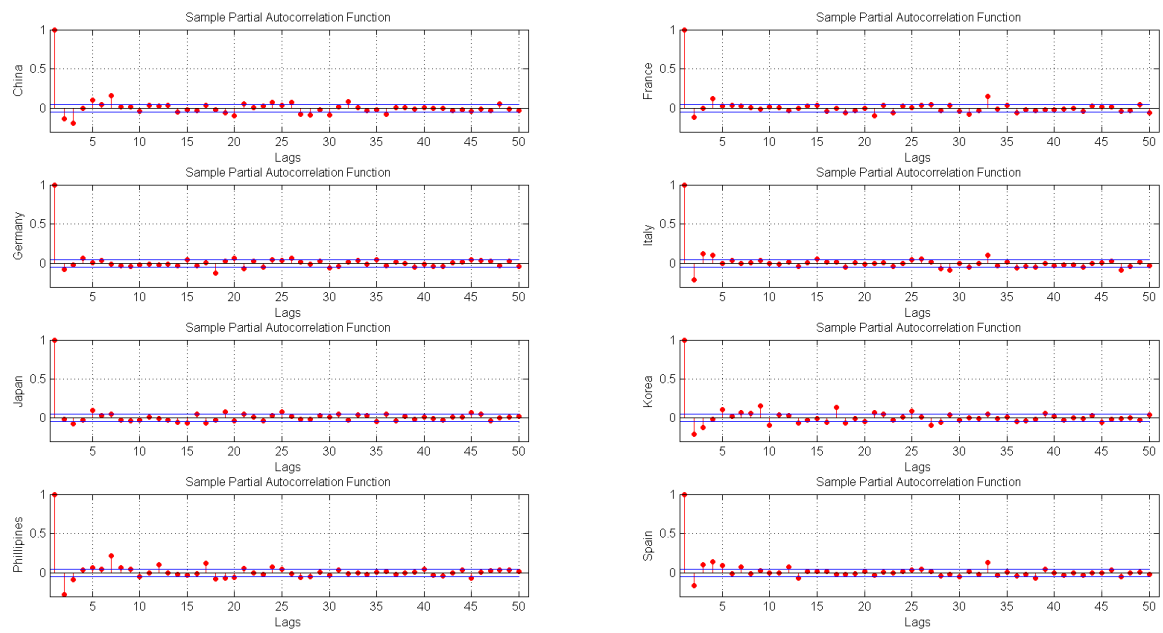
Figure 3: Partial Autocorrelations of Daily Sovereign CDS Spreads from Lag 1 to Lag 50

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Figure 4: Q-Q Plots of Daily Sovereign CDS Spreads against Normal Distribution

and standard deviation of the CDS spreads for each country tend to correlate with the credit quality in the respective country. That is, the higher credit rating of the country, the lower the spreads of its sovereign CDS contracts. This pattern makes sense considering the nature of the sovereign CDS spreads. As pointed out by Bluhm et al. (2002), credit rating of a country represents its creditworthiness, and a low credit rating indicates a high default probability on its debts. It is the sovereign CDS contracts that protect investors from this default risk on the sovereign bonds. To be sure the contract prices, namely the CDS spreads, are higher for countries with higher default probabilities. Especially, when these countries undergo drastic changes in credit qualities, their sovereign CDS spreads will become more volatile. The above observation applies to the sovereign CDS spreads both before and after the crisis. As we can see from Table 2, the average spread for the Philippines is almost twice its size as the second largest average spread among the included countries. Recall that except for the Philippines, all of these countries had good records of credit qualities before the 2008-2009 crisis, reflected in the relatively low levels of their sovereign credit spreads in Figure 1. Nevertheless, after the crisis, due to the increased global credit risks and the generally downgraded credit ratings elsewhere, all of these countries

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Table 3: Correlation Matrix for Daily Changes of Sovereign CDS Spread

Time Period		China	France	Germany	Italy	Japan	Korea	Philippines	Spain
	China	1	0.246	0.269	0.258	0.357	0.787	0.7283	0.225
	France	0.246	1	0.709	0.726	0.210	0.222	0.203	0.660
	Germany	0.269	0.709	1	0.581	0.212	0.249	0.236	0.51
Sept 2004 - Aug 2012	Italy	0.258	0.726	0.581	1	0.216	0.224	0.211	0.824
	Japan	0.357	0.21	0.212	0.216	1	0.363	0.263	0.147
	Korea	0.787	0.222	0.249	0.224	0.363	1	0.798	0.205
	Philippines	0.728	0.203	0.236	0.211	0.263	0.798	1	0.181
	Spain	0.225	0.66	0.51	0.824	0.147	0.205	0.181	1
		China	France	Germany	Italy	Japan	Korea	Philippines	Spain
	China	1	0.116	-0.007	0.139	0.098	0.544	0.371	0.058
	France	0.116	1	0.033	0.03	0.06	0.125	0.036	0.021
	Germany	-0.007	0.033	1	0.048	-0.104	-0.003	0.005	-0.013
Sept 2004 - Aug 2008	Italy	0.139	0.03	0.048	1	0.07	0.11	0.058	0.528
	Japan	0.098	0.06	-0.104	0.07	1	0.125	0.039	-0.016
	Korea	0.544	0.125	-0.003	0.11	0.125	1	0.365	0.063
	Philippines	0.371	0.036	0.005	0.058	0.039	0.365	1	0.031
	Spain	0.058	0.021	-0.013	0.528	-0.016	0.063	0.031	1
		China	France	Germany	Italy	Japan	Korea	Philippines	Spain
	China	1	0.254	0.309	0.266	0.372	0.805	0.78	0.234
	France	0.254	1	0.789	0.738	0.214	0.225	0.222	0.671
	Germany	0.309	0.789	1	0.639	0.243	0.277	0.281	0.562
Sept 2008 - Aug 2012	Italy	0.266	0.738	0.639	1	0.219	0.226	0.229	0.825
	Japan	0.372	0.214	0.243	0.219	1	0.37	0.288	0.149
	Korea	0.805	0.225	0.277	0.226	0.37	1	0.856	0.207
	Philippines	0.78	0.222	0.281	0.229	0.288	0.856	1	0.197
	Spain	0.234	0.671	0.562	0.825	0.149	0.207	0.197	1

find themselves to be in relatively better ratings; this is especially the case for Italy and Spain. Korea is the only exception to the case in terms of the contrast between its relatively good A+ credit quality and its large range and maximum values of the sovereign CDS spreads. It should be pointed out that Korea's credit rating was upgraded three times during the 2008-2009 period, apparently due to reduced geopolitical risks associated with a smooth transition of leadership in North Korea. Despite its new updated A+ rating, South Korea was affected by the development in North Korea for most part of the sample period, which explains its wide range of the credit spreads. It is also noticeable that all of these countries have much larger values of standard deviation compared with the values of the mean. Half of them have larger values of standard deviation relative to the average values of spreads. This is indicative of substantial time-series variations during the sample period for our study.

Cross-correlation tests on the daily changes of the sovereign CDS spreads suggest

that these spread are pairwise correlated. The sample correlation matrices are calculated and reported in Table 3. As shown in Table 2, these countries have different sizes of sample data, so their sample correlation are calculated based on the days in which the spreads overlap. Moreover, to further check the nature of the sovereign CDS spreads and analyze the potential changes in their co-movements before and after the crisis, we divide the eight-year sample period into two sub-periods which correspond to the pre-crisis period from September 2004 to August 2008, and the post-crisis period from September 2008 to August 2012.

The first part of Table 3 presents their sample correlation coefficients over the full sample. From this table, it is evident that the sovereign CDS spreads are pairwise positively correlated, providing evidence for their co-movements. Besides, we notice that the pairwise correlations between any two countries in the same region tends to be stronger than those in different regions. For example, the correlations between China and other Asian countries are larger than the correlations between China and any European countries; while France is much more strongly correlated with Germany, Italy, and Spain than with any of the Asian countries (Average: 70% vs 22%). These results, taken together, suggest that the regional factor is likely to be an important determinant for the sovereign credit risk in these countries.

The second and third parts of Table 3 show the sample correlation matrices for the sovereign CDS spreads in the pre and post-crisis periods respectively. Quite notably the pairwise correlations have increased after the 2008-2009 global financial crisis. The average correlation between the sovereign CDS spreads is about 10% during the period from September 2004 to August 2008, but it increases to a whopping 41% during the period from September 2008 to August 2012.

The most dramatic changes in the correlation between the sovereign CDS spreads are observed between Germany and Asian countries. Before the crisis, the changes of the sovereign CDS spreads of Germany were negatively correlated with those of China, Japan, Korea and Spain. These sample correlations switch sign to be positive after the crisis. Consistent with the above findings, recently Dahlquist and Hasseltoft (2011) also observed increased correlations between international bond risk premia. We take this as evidence of increased systematic sovereign credit risk in the global financial markets, as well as increased integration between the financial markets following the crisis. This also confirms the findings reported in Ang and Bekaert (2002) about the tendency for the correlations between international financial markets to increase during the periods of highly volatile bear markets.

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3 PCA of Sovereign CDS Spreads

Given that the the sovereign CDS spreads have been found to be pair-wise correlated, in this section, we focus on identifying the commonality of these spreads. That is, we use a principal components analysis (PCA) to investigate the daily changes in the sovereign credit spreads. For reference, we also conduct the same analysis on the stock index returns for the countries, and interpret the PCA result by calculating its sample correlation coefficients included in this study with several US stock indices as well. In the PCA, the data set is transformed into a set of principal components (PCs), which forms a new set of ordered uncorrelated variables. By conducting the PCA on the covariance matrices of daily sovereign credit spread changes, we are able to identify the commonality in these CDS premiums. Similar to Table 3, the covariance matrices are based on the overlapping daily spreads data, and calculated for the full sample as well as the pre and post-crisis samples respectively. In this way, we can compare the latent changes in the global sovereign CDS markets over these two subperiods, since our previous analysis has uncovered evidence of increased correlations among the spreads after the crisis.

To provide further analysis, we also use the data set for domestic equity indices for the eight countries as a reference point. This reference set describes the returns of local stock markets. The description for these equity indices, which are retireved from the Bloomberg data base, can be found in Appendix A.

Before proceeding to dicuss the PCA results, we first calculate pairwise correlations between these index returns for the full and two sub-samples. These are shown in Table 4. Similar to the sample correlation matrix of the CDS spread changes, there appear to be strong correlations between the index returns, and the pairwise correlations between the indices in the same region also tends to be larger than those for indices across the two regions. However, there are noticeable differences between the two correlation matrices: For both subsamples, the pairwise correlations between the index returns are always positive, which is is not the case with the correlation matrix for the CDS spreads in the pre-crisis period. The average values for the indices in the two subsamples are quite close to each other (40% vs 45%), while there is a huge increase in the average values for the spread changes (10% vs 41%). This suggests seemingly important differences in the correlation structure between the sovereign CDS spreads and the local equity returns. Other than local equity returns, variables such as other global economic and regional factors may also influence the changes of the sovereign credit spreads.

Based on the results from the correlation matrices, we conduct the PCA on daily changes of both the sovereign CDS spreads and the local stock markets daily returns.

Table 4: Correlation Matrix for Local Index Returns

Time Period		China	France	Germany	Italy	Japan	Korea	Philippines	Spain
		China	France	Germany	Italy	Japan	Korea	Philippines	Spain
	China	1	0.17	0.175	0.152	0.278	0.318	0.192	0.137
	France	0.17	1	0.936	0.917	0.365	0.368	0.213	0.882
	Germany	0.175	0.936	1	0.865	0.347	0.394	0.198	0.822
Sept 2004 - Aug 2012	Italy	0.152	0.917	0.865	1	0.316	0.324	0.189	0.893
	Japan	0.278	0.365	0.347	0.316	1	0.676	0.452	0.314
	Korea	0.318	0.368	0.394	0.324	0.676	1	0.446	0.317
	Philippines	0.192	0.213	0.198	0.189	0.452	0.446	1	0.176
	Spain	0.137	0.882	0.822	0.893	0.314	0.317	0.176	1
		China	France	Germany	Italy	Japan	Korea	Philippines	Spain
	China	1	0.085	0.103	0.098	0.22	0.242	0.128	0.078
	France	0.085	1	0.947	0.919	0.348	0.339	0.184	0.906
	Germany	0.103	0.947	1	0.903	0.352	0.348	0.192	0.892
Sept 2004 - Aug 2008	Italy	0.098	0.919	0.903	1	0.313	0.318	0.181	0.877
	Japan	0.22	0.348	0.352	0.313	1	0.673	0.401	0.315
	Korea	0.242	0.339	0.348	0.318	0.673	1	0.409	0.302
	Philippines	0.128	0.184	0.192	0.181	0.401	0.409	1	0.177
	Spain	0.078	0.906	0.892	0.877	0.315	0.302	0.177	1
		China	France	Germany	Italy	Japan	Korea	Philippines	Spain
	China	1	0.249	0.245	0.207	0.346	0.404	0.273	0.193
	France	0.249	1	0.931	0.922	0.374	0.383	0.242	0.876
	Germany	0.245	0.931	1	0.859	0.346	0.418	0.213	0.801
Sept 2008 - Aug 2012	Italy	0.207	0.922	0.859	1	0.324	0.334	0.213	0.898
	Japan	0.346	0.374	0.346	0.324	1	0.677	0.5	0.317
	Korea	0.404	0.383	0.418	0.334	0.677	1	0.484	0.328
	Philippines	0.273	0.242	0.213	0.213	0.5	0.484	1	0.19
	Spain	0.193	0.876	0.801	0.898	0.317	0.328	0.19	1

Time Period	Sovereign CDS Spreads			Local Stock Returns		
	PCs	% Explained	Total	PCs	% Explained	Total
	1st	46.96	46.96	1st	53.06	53.06
	2nd	25.00	71.96	2nd	20.75	73.81
Sept 2004-Aug 2012	3rd	10.21	82.17	3rd	10.29	84.10
	4th	7.04	89.21	4th	7.60	91.70
	5th	3.31	92.53	5th	4.16	95.86
	PCs	% Explained	Total	PCs	% Explained	Total
	1st	25.07	25.07	1st	52.14	52.14
	2nd	18.12	43.19	2nd	20.95	73.09
Sept 2004-Aug 2008	3rd	13.65	56.83	3rd	11.16	84.25
	4th	12.52	69.36	4th	8.14	92.40
	5th	10.90	80.26	5th	4.07	96.47
	PCs	% Explained	Total	PCs	% Explained	Total
	1st	48.95	48.95	1st	54.46	54.46
	2nd	25.48	74.43	2nd	20.90	75.36
Sept 2008-Aug 2012	3rd	10.11	84.54	3rd	9.12	84.48
	4th	6.48	91.01	4th	7.19	91.66
	5th	2.83	93.85	5th	4.17	95.83

Table 5 presents the results for the full and two sub-samples. For the sovereign CDS spreads, the PCA results provides strong evidence of commonality during the full sample. In fact, the first PC explains 46.96% of the variation of the sovereign credit spreads, and the first three PCs explains over 80% of the variation. Here, we define the commonality of sovereign CDS spreads as the variations explained by the first three PCs.

There are substantial differences in the first and second PCs during the periods before and after the financial crisis. In the pre-crisis period, the first PC itself only explains 25.07% of the variation, while the second PC explains about 18% of the variation. However, over the post-crisis period, the explanatory power of the first PC increases to a whopping 48.95%, while the second PC accounts for more than 25% of the spread variation. Looking at the total percentage explained by the first two PCs, we see that part of the explanatory power of the other PCs are absorbed by the first two PCs in the post-crisis period. The increased commonality among the spreads after the crisis is consistent with the argument made by Ang and Bekaert (2002) about tendency of increased correlations among international financial markets mentioned earlier.

Next, we turn our attention to the local stock returns. Over the full sample, the first PC explains 53.06% of the variation, and the first three PCs explains almost

85% of the variation in total. Thus, there is even stronger evidence of commonality in the behavior of the local stock markets for the eight countries. Besides, in contrast to the results for the CDS spreads, there is basically no change on the percentage explained by each PC of the stock returns over the pre and post-crisis periods, with the total percentage explained by the first three PCs remaining more or less stable at around 85%. This is an additional piece of evidence pointing at the structural differences between the sovereign credit spreads and the local stock market returns.

Figure 5 plots the loadings for the first three PCs for the full, the pre-crisis, and the post-crisis samples. Consistent with the results in Table 5, the loadings for the full sample are quite close to those of the post-crisis period.

Focusing now on the full sample, we see that the loadings for the first PC follow roughly a uniform distribution. This indicates that the first PC represents certain global factors, and these global factors have similar influences on the sovereign credit spreads for different countries. As for the second PC, all of the loadings for the Asian countries are positive, while those for the European countries are negative. One possible explanation for this result is that the second PC captures the influence of regional factors.

To further interpret the first two PCs, we calculate the sample correlations from their time series with several indices. For the time series of the first PC, its sample correlation coefficient with the daily return of the S&P500 is -33.34%, its sample correlation coefficient with the daily return of the Dow Jones Industrial Average is -33.05%, its sample correlation coefficient with the daily return of the NASDAQ Composite Index is -30.16%, and its sample correlation coefficient with the daily changes of the VIX index is 34.65%.

Thus, it is safe to conclude that the first principal variation source of the sovereign CDS spreads is at least partially correlated with the U.S. stock markets measured by various stock indices and equity market volatility. This is consistent with the findings in Longstaff et al. (2011), who report a strong negative correlation between the first PC and the U.S. stock markets.

For the time series of the second PC, we calculate the difference between the daily return of the EURO STOXX Index[6] and the daily return of the MSCI Asia APEX 50 Index as a proxy for the regional economic factors. This measures the difference in daily market performances between EMU and Asian equity markets. The sample correlation between this proxy and the time series of the second PC is -34.51% over the full sample, and is -39.29% over the latter part of the sample, which, to some

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[6]The EURO STOXX (Price) Index is a capitalization-weighted index which includes countries that are participating in the EMU. MSCI Asia APEX 50 Index is a free float-adjusted, market capitalization weighted index, which is considered a benchmark by most investors in Asia.
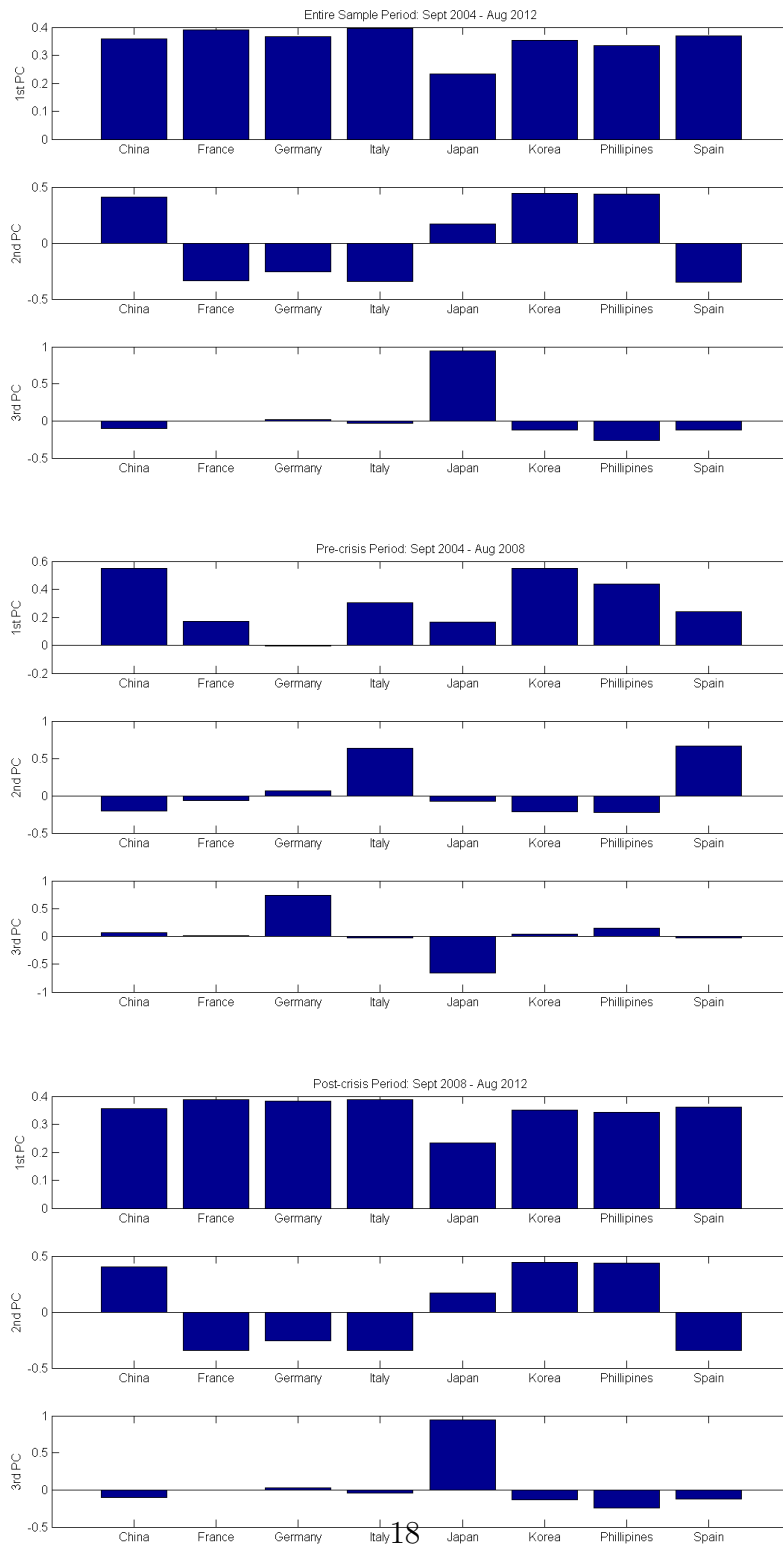
Figure 5: Loadings for First Three PCs of Daily Sovereign CDS Spreads Changes

extent, reinforces our previous result for the second PC.

4 Sources of Commonality

According to McGuire and Schrijvers (2003), the spreads of co-movements on bond debt across countries suggest that they are driven by one or more common factors. This is consistent with our analyses in the last section, which provide strong evidence of commonality among the changes of the sovereign credit spreads. So, as a next step in this section, we seek to determine the sources of this commonality. Using a similar exploration technique to the one presented in Longstaff et al. (2011), we introduce a combined set of local economic variables and global macroeconomic factors, and investigate their impacts on the sovereign credit risk. As it is difficult to collect the daily data for some macroeconomic factors, we use monthly data to analyze the commonality among the sovereign CDS spreads.

4.1 Choices of Explanatory Variables

We rely on previous studies in the literature to identify a set of economic variables that may affect the sovereign credit risks. According to Grossman and Van Huyck (1988), the defaults of sovereign debts were related to the bad states of the economy. McGuire and Schrijvers (2003) argued that a common variation in the emerging-market debt spreads can be largely explained by investors' attitudes towards risks. The study of Baek et al. (2005) showed the importance of economic fundamentals and market's risk attitudes on the sovereign risk premiums. Similarly, Remolona et al. (2008) decomposed the sovereign CDS spreads into expected losses from default and market risk premia required by investors as compensation for default risk. Their results indicated some associations between the sovereign credit risk and the country-specific fundamentals as well as the global investors' risk aversion. Baldacci et al. (2008) focused on the determinants of the sovereign CDS spreads in the emerging markets, and found that both fiscal and political factors mattered for the sovereign credit risk. Attinasi et al. (2009) also pointed out the vital role of fiscal fundamentals on the widening sovereign spreads in Europe during the 2008-2009 financial crisis. The results in Hilscher and Nosbusch (2010) highlighted the importance of global economic factors, such as implied volatility of VIX index and US Treasury yield, and the substantial explanatory power of country-specific factors, on the emerging markets' sovereign CDS spreads. Augustin and Tédongap (2011) developed a sovereign CDS pricing model, which links sovereign credit risk premia to consumption growth forecasts and macroeconomic uncertainty.

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We start with a set of local and global economic factors as candidates for the explanatory variables in our regressions. Risk premium is included as an important source of the sovereign CDS spreads in our regressions. In addition, we also note that some prior studies have focused mainly on the emerging markets (see e.g. Remolona et al., 2007, Baldacci et al., 2008, Hilscher and Nosbusch, 2010), while some other prior studies have considered European markets only (e.g. Attinasi et al., 2009). In this paper, we construct the sovereign CDS data from selected Asian and European countries, where Asian countries are treated as emerging markets and European countries as developed markets. Against this background, and considering the previous PC analysis results, we take the regional factors into account in our analysis as well.

4.1.1 Local Economic Variables

Following Longstaff et al. (2011), we select local equity markets returns, changes in the exchange rate, and changes in the foreign-exchange reserves to proxy the state of the local economy.

Local Stock Market - It is well known that the stock market serves as an indicator for the overall economic condition. When the stock market rallies, people become wealthier and spend more, and, as a result, investment spending is stimulated as well (Mankiw, 2011). As mentioned in Section 3, we calculate the monthly returns of the local stock markets for the eight countries for a period from September 2004 to August 2012 via the corresponding local equity indices. All of the indices are denominated in units of local currencies.

Exchange Rate - By interacting with other economies in the world through buying and selling goods and services in world product markets and capital assets in world financial markets, an open economy is influenced to a large extent by its exchange rates, which measure the prices of these international transactions (Mankiw, 2011). Thus, the exchange rate is considered a good proxy candidate for the local economic factors.

According to Aristovnik and Čeč (2009), most raw materials are now traded in U.S. dollars, and this currency covers more than four-fifths of foreign trades and one-half of global exports. That is, U.S. dollar is widely accepted as the world currency. We define the exchange rate as the value of one unit of the local currency in terms of the U.S. dollar. The data for the exchange rates are obtained from the Bloomberg data base. Then we calculate their monthly percentage changes to be used in our regression analyses. We note that in some instances there are not much temporal variations in the exchange rates. For example the CNY/USD rate remains steadily

at 0.1208 from September 2004 to March 2005. In this case, a zero percentage change is entered into the data.

Foreign-exchange Reserves - Foreign-exchange reserves refer to foreign currency deposits and bonds held by central banks. Thus, the changes in the foreign-exchange reserve reflect the monetary policies of the central banks (Aristovnik and Čeč, 2009). Central banks typically use the foreign-exchange reserves to stabilize the value of domestic currency and control foreign exchange rates, provide proper amounts of international payments, support a favorable economic environment, and reduce the risks of speculatively induced collapse (Palley, 2004). In addition to these roles, there is an apparent linkage between foreign reserve and local economy; that is, countries must hold adequate foreign-exchange reserves to service their foreign debt obligations. So, foreign-exchange reserves are also a measure of liquidity (Remolona et al., 2008). The higher the reserves are, the lower the sovereign risk expected to be.

Given this indirect relationship, we also include the percentage changes of foreign-exchange reserves as one of the local economic variables. The data is again obtained from the Bloomberg data base, which are collected from National Bureau of Statistics of China, Ministry of Finance Japan, Bank of Korea, Banko Sentral ng Philipinas (Central Bank of the Philippines) and Eurostat respectively. All of the foreign reserves are denominated in the US dollar.

4.1.2 Global Financial Market Variables

As mentioned earlier, all of the countries included in our study are open economies and they interact with other economies in global markets. Thus, their sovereign credit risks and risk premiums rely not only on their local economic states, but also on their global macroeconomic factors. Moreover, steadily increased globalization has contributed to the world economy with increased financial direct investments and multinational companies, and reduced trade barriers, foreign exchange limits and government restrictions since the end of the twentieth century. Globalization has also increasingly shaped polices and behaviors of countries and regions, which tends to increase the dependence of the open economies on global factors. As Mauro et al. (2002) stated, nowadays drastic changes in sovereign bonds tend to be mostly related to global events than country-specific events, and this correlation tends to be stronger than they were historically.

Unlike the local economy factors, it is more difficult to find suitable candidates for global macroeconomic factors. In order to capture the general characteristics and broad movements of global economy, we use measures of U.S. economy as proxies as

suggested by Longstaff et al. (2011). As the world's largest economy, the U.S. plays a vital role in the global economic and financial markets. Additionally, U.S. is not included in the eight countries selected in our study. Some studies have reported high correlation between the U.S. equity market and other major equity markets, and the considerable impact of the U.S. stock market on global equity markets (See, for instance, Arshanapalli and Doukas, 1993 and Goetzmann et al., 2005).

Global Stock Market - Similar to the local variables, we treat the global stock market as the key variable to proxy for the global financial market variables. To estimate the global stock market, we include the Wilshire 5000 Total Market Index as a proxy. This capitalization-weighted index aims at measuring the performance of the entire U.S. stock market by including all of the U.S. headquartered equity securities with readily available price data. Unlike the calculation of the local stock market returns, we calculate the excess returns of this index by deducting the U.S. one-month Treasury bill rate from the index return rates. Following Fama and French (1993), the one-month Treasury bill rate plays the role of the risk-free interest rate in this case. The data is obtained from the Bloomberg data base with the symbol: USGG1M.

Global Treasury Market - Compared with the stock market, the fixed income market provides sovereigns, corporates and investors another source for funding. Global financial market participants benefit from the softened impact of a limited access to capital markets or bank credit, as well as more choices of instruments to deal with inherent currency and maturity mismatches (Eichengreen and Hausmann, 1999). Over the past fifteen years, the global bond market has reached a vast capitalization of over \$80 trillion, which goes far beyond the \$55 trillion capitalization of its stock market counterpart. For the bond market, the U.S. portion covers a capitalization of over \$30 trillion, according to Fitz-Gerald (2011).

Given the above arguments, it is essential to include this large and dominant market in the list of the global economic variables. Following Longstaff et al. (2011), we use the changes in the U.S. five-year Constant Maturity Treasury (CMT) yield to capture the fluctuations in the global treasury market and signal the global economic tendencies. Considering the foreign reserve role of Treasury bonds to many countries, this variable might also contain a liquidity component. The data is reported as part of the H.15 Federal Reserve Statistical Release, and is obtained from the Bloomberg data base under the symbol: CMAT05Y.

Investment-grade & High Yield Bonds - Investors sometimes like to redistribute their capitals across different markets, asset classes and regions. Thus, in addition to the stock and treasury markets, the shifts in the relative liquidity over time could also make a difference to the prices of instruments in the global financial market.

The movements in the the spreads of investment-grade bonds and high-yield bonds serve to reflect the attitudes of investors in the economy.

For the investment-grade and high-yield bonds, it is desirable to use relevant indices, such as the well-known CDX indices that are composed of equally weighted credit default swaps on investment-grade and high-yield entities. However, the CDX data is not available for the entire sample period for our study. The next-best available proxies for this are the spreads between BBB- and AAA- rated bonds, and the spreads between BB- and BBB- rated bonds. By calculating their monthly changes, we obtain two variables that serve to capture the variations in investment-grade and high-yield bonds respectively. Specifically, these corporate bond yields come from the US five-year industrial AAA-, BBB- and BB- rated bond indices. These fair market value indices are derived from data points on option-free Fair Market Curves by Bloomberg, and represent the average yields for noncallable bonds within corresponding credit ratings and with five years' maturity. However, there is still a remaining issue in measuring this variable, which is associated with the five-year Industrial AAA bond index being discontinued on March 2012.[7] So, for the four month periods from April 2012 to August 2012, we instead simulate the monthly spread changes for investment-grade bonds based on the monthly returns of CDX investment-grade five-year index.

4.1.3 Global Risk Premiums

As mentioned earlier, in the literature on the determinants of corporate and sovereign credit spreads, there is an issue on how to appropriately measure these common external factors, which are essentially the default risk components, comprised of a set of fundamental variables determining creditworthiness. In this regard, many researchers also have noticed the phenomenon of a so-called credit spread puzzle. This phenomenon refers to the case where the component of credit spreads driven by the default risk factors only accounts for parts of the sovereign credit spreads.

For instance, in the corporate credit spread literature, Berndt et al. (2008) and Driessen (2005) decomposed corporate bond spreads into expected losses from default and the default risk premium. The latter is also referred to as the price of default risk, which is the financial compensation required by investors for bearing relevant risks. Their empirical research not only confirmed the significant risk premia on common

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[7]According to Bloomberg analysts we talked to during the course of this research, a possible reason for this index to be discontinued index is due to the widespread downgrading of these original AAA corporate bonds after the crisis. As a result, there are not enough AAA rated bonds in the U.S. treasury market to calculate the index.

intensity factors, but also found a substantial variation in the risk premia over time. Similarly, in the sovereign credit spread literature, Baek et al. (2005), Remolona et al. (2008), and Augustin and Tédongap (2011) regarded sovereign credit spreads as "a measure of a country's creditworthiness" plus a measure of risk premia as demanded compensation for sovereign default risks, with the risk premia accounting for an even larger component of the sovereign spreads.

Based on the above discussion, we conclude that the sovereign credit risk spreads are driven by the level of sovereign risks as well as the prices for bearing the risks. The former is determined by both the local and global economic fundamentals, while the latter represents investors' general attitudes towards risks, which can vary quite considerably over time. So, in this section, we include the global risk premiums as one of the explanatory variables in our regressions in addition to the local and global macroeconomic factors. For consistency, we include the risk premiums for stock market, treasury market and volatility. As in the last section, we also use the data of the U.S. markets to represent global variables.

Equity Risk Premium - Following Longstaff et al. (2011), we use the the earnings-price (E/P) ratio of S&P 500 Index as a proxy for equity risk premium.[8] Although admittedly simplistic, the changes in this E/P ratio do reflect variations of the equity risk premiums, which is often used in the asset-pricing literature as a model-free measure. The monthly E/P ratio of S&P 500 Index is obtained from the Bloomberg data base.

Bond Risk Premium - As a proxy for the variation of bond risk premium, we calculate the changes in expected excess return on five-year U.S. Treasury bonds based on a linear model used in Cochrane and Piazzesi (2002). Specifically, they used a single tent-shaped linear combination of forward rates to compute excess returns on one to five-year maturity bonds. They also provided estimated parameters of the single-factor model based on Fama-Bliss data. Since Fama-Bliss data is not available after December 2006, we use the one to five-year U.S. Treasury Strip data obtained from Bloomberg's option-free Fair Market Curves instead. Based on the primary data, we first construct the term structure of forward rates, then substitute them into the linear model, and obtain monthly changes in bond risk premium.

Volatility Risk Premium - Unlike the risk premiums for equities and bonds, the volatility risk premium (VRP) is considered to be a function of both the price of the underlying asset and its volatility, according to Sugihara (2010). That is, the price of volatility risk consists of not only the components of uncertainty in future

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[8]Longstaff et al. (2011) used the E/P ratio and other data for S&P 100 Index in calculating the risk premiums. However, to be consistent with the VIX index in this section, we use the data of S&P 500 Index instead.

asset price levels, but also the components of uncertainty in future volatilities. VRP is defined as the difference between the squared implied volatility under the risk neutral measure and the squared realized volatility in the real world given a period of observations:

$$
\begin{aligned}
VRP &= (\text{Implied Volatility})^2 - (\text{Realized Volatility})^2 \\
&= \text{Implied Variance} - \text{Realized Variance}.
\end{aligned}
\tag{1}
$$

For the implied variance, we use the month-end VIX index, which is a widely used measure for the implied volatility of S&P 500 Index under the risk-neutral measure by financial economists, risk managers and volatility traders. To be specific, this index represents the annualized expected volatility of S&P 500 Index over the next 30-day period, which is quoted in percentage points and traded on the Chicago Board Options Exchange (Exchange, 2009). Thus, the annualized implied variance is calculated as:

$$
\text{Implied Variance} = (\frac{VIX}{100})^2
\tag{2}
$$

Realized volatility plays an important role in derivative pricing and portfolio risk management (Merton and Samuelson, 1990). The primary method to estimate the realized volatility is based on the close-to-close prices. To attain higher accuracy, sophisticated estimators have been developed using additional information such as high, low, close and open prices (Yang and Zhang, 2000; Garman and Klass, 1980; Yang and Zhang, 2000; Floros, 2009). Below we briefly review these estimators. First, we introduce the following notations:[9]

f: fraction of the period (interval [0,1]) that trading is closed;
V: unknown variance of a price change, namely σ^2;
C_0: closing price from previous period (at time 0);
C_1: closing price for current period (at time 1);
O_1: opening price for current period (at time f);
H_1: current period's high price during the interval $[f,1]$;
L_1: current period's low price during the interval $[f,1]$;
o: $lnO_1 - lnC_0$, the normalized open;
c: $lnC_1 - lnO_1$, the normalized close;
u: $lnH_1 - lnO_1$, the normalized high;
d: $lnL_1 - lnO_1$, the normalized low;

---

[9]The notations here are consistent with those of Garman and Klass (1980), Yang and Zhang (2000), and Floros (2009).

For an n-period historical data set, the classical close-to-close variance estimator V_{cc}) can be written as:

$$V_{cc} = \frac{1}{n-1}\sum_{i=1}^{n}[(o_i + c_i) - \frac{1}{n}\sum_{i=1}^{n}(o_i + c_i)]^2 \tag{3}$$

Parkinson (1980) introduced an estimator involving high and low prices as:

$$V_P = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{4ln2}(u_i - d_i)^2. \tag{4}$$

Another variance estimator involving high-low-close prices was developed by Rogers and Satchell (1991), which can be expressed as:

$$V_{RS} = \frac{1}{n}\sum_{i=1}^{n}[u_i(u_i - c_i) + d_i(d_i - c_i)]. \tag{5}$$

Garman and Klass (1980) derived a widely used estimator based on high-low-open-close prices as:

$$V_{GK} = \frac{1}{n}\sum_{i=1}^{n}o_i^2 - 0.383\frac{1}{n}\sum_{i=1}^{n}c_i^2 + 1.364V_P + 0.019V_{RS}. \tag{6}$$

More recently, Yang and Zhang (2000) proposed a minimum-variance unbiased variance estimator, which is independent of the drift term and the opening jump as:

$$V_{YZ} = V_O + kV_C + (1-k)V_{RS}, \tag{7}$$

where

$$V_O = \frac{1}{n-1}\sum_{i=1}^{n}(o_i - \frac{1}{n}\sum_{i=1}^{n}o_i)^2, \tag{8}$$

$$V_C = \frac{1}{n-1}\sum_{i=1}^{n}(c_i - \frac{1}{n}\sum_{i=1}^{n}c_i)^2, \tag{9}$$

$$k = \frac{\alpha - 1}{\alpha + \frac{n+1}{n-1}}, \tag{10}$$

with α=1.34 set in practice.

As argued by Yang and Zhang (2000), their estimator has several advantages over other existing estimators. It is unbiased and independent of both the drift and the opening jumps, and it has the minimum variance and highest efficiency among estimators with similar properties. For this reason, we use the estimator in Equation (7) to compute realized volatility.[10]

To be consistent with the VIX index, which estimates the implied volatility of S&P 500 Index over the next month, we calculate a rolling 21-day (n=21) estimator of realized volatility[11] on the high, low, open and close prices of S&P 500 Index. The annualized volatility risk premium is computed as:

$$
\begin{aligned}
VRP &= \text{Implied Variance} - \text{Realized Variance} \\
&= (\frac{VIX}{100})^2 - 252V_{YZ}.
\end{aligned}
\tag{11}
$$

4.1.4 Regional Sovereign Spreads

The results from the correlation matrices and PCAs in Sections 2 and 3 revealed a comparable size of correlations between the sovereign credit spreads of countries from the same geographic region, and indicate a potentially important influence of the regional factors on the sovereign CDS spreads. As a proxy for the underlying regional factor, we include certain measures of regional sovereign spreads in our regressions. Specifically, since all of the countries studied in this paper come from either Asia or Europe, the two variables are termed an Asian Spread and a European Spread. For each of the selected country, its Asian Spread and European Spread are obtained in the manner described below.

In the case of China, first we need to calculate the average sovereign CDS spreads in Asia and Europe separately. Since China locates in Asia, when we deal with the average Asian spread, it is necessary to exclude China and compute only the average spreads for the other three countries in this region. Note that we could not use these average spreads directly in the regressions, because there would be double counting of the same information contained in the regional spreads and other variables, such as the shocks of global economic variables, which have already been incorporated in our regression specification. Further steps are taken to eliminate this double counting

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[10]As a robustness check, we also calculate the volatility risk premium using the estimator proposed by Garman and Klass (1980). The regression results from this estimation are very similar to those reported here.

[11]Usually, it is assumed that there are 21 trading days a month and 252 trading days a year in average.

of information and to represent the regional impact more accurately. This is done by regressing the monthly changes of the average regional spreads on all of the other explanatory variables using the ordinary least square (OLS) method. In this way, we obtain orthogonalized residuals from the regression, representing additional regional variables.

4.2 Regression Analyses

For each of the eight countries studied in this paper, we regress the monthly changes of their sovereign CDS spreads on the local and global variables. Table 6 presents the autocorrelation and heteroskedasticity robust t-statistics for each explanatory variable based on the procedure advocated by Newey and West (1987) with data-determined lags,[12] and the adjusted R^2 for each regression. In addition, for each part of the variables, the table also reports a ratio, which measures the proportion of the total variation explained by the regression that is due solely to this part of variables. For instance, for the ratio for local variables, we first regress changes in sovereign CDS spreads only on the local variables and obtain the R^2 from this regression. We then divide this R^2 by the R^2 from the full regression with all the variables included. Because the local variables are not orthogonal to other variables, this ratio should be viewed as an upper bound for the proportion (Longstaff et al., 2011).

---

[12]Longstaff et al. (2011) reported the t-statistics based on heteroskedasticity consistent covariance matrix estimates of White (1980). However, we argue that autocorrelation would also be a relevant issue for the error terms of our regressions.

Table 6: t-Statistics and Other Regression Results

	China	France	Germany	Italy	Japan	Korea	Philippines	Spain
Local Variables								
Stock Market	-2.633**	-4.517**	-0.904	-6.770**	-0.362	-2.769**	-3.207**	-5.821**
Exchange Rate	-0.246	-3.710**	0.338	-5.767**	-1.280	-3.365**	-1.986*	-2.562**
Foreign Reserve	0.349	-2.328**	-0.337	-2.620**	3.108**	0.019	-0.418	3.059**
Ratio	0.323	0.607	0.421	0.605	0.453	0.738	0.629	0.676
Global Variables								
Stock Market	-1.901*	2.989**	-0.249	2.076**	-1.775*	-0.953	-0.295	2.683**
Treasury Market	0.305	-0.404	1.580	-2.400**	0.162	1.812*	0.218	0.080
Investment Grade	2.589**	1.385	0.328	1.960*	1.270	1.738*	1.439	-0.043
High Yield	2.774**	0.728	1.376	-1.332	-0.235	2.295**	0.549	0.472
Ratio	0.707	0.452	0.528	0.340	0.637	0.711	0.678	0.199
Global Risk Premiums								
Equity Premium	0.529	3.806**	2.862**	0.531	-0.124	-0.485	2.231**	1.163
Volatility Premium	2.934**	-0.654	0.340	-0.208	1.318	3.484**	4.800**	-0.337
Bond Premium	2.397**	-1.044	-0.260	0.667	1.125	-0.903	-2.856**	0.876
Ratio	0.531	0.412	0.501	0.240	0.512	0.715	0.700	0.201
Sovereign Spreads								
Asian Region	7.611**	2.227**	3.695**	1.081	3.300**	4.423**	4.910**	-1.616
European Region	1.125	8.076**	1.377	7.467**	1.288	-0.334	0.375	5.154**
Ratio	0.196	0.317	0.379	0.322	0.179	0.114	0.090	0.240
Adjusted-R Square	0.801	0.686	0.351	0.772	0.488	0.807	0.669	0.716

[1] Note: The ratio for each part represents the R^2 from the regression where only this part of variables are included over the R^2 from the regression where all the variables are included.

** Significant at the level of 5%.

* Significant at the level of 10%.

As shown in the table, the adjusted R^2s are generally high, with the exception for Germany with a relative low adjusted R^2 of 35.1%. The adjusted R^2 for the regression for Japan is recorded at 48.8%. All of the adjusted R^2s from other regressions are larger than 65%. This is taken as evidence that these explained part of the regression captures most of the observed variations in the sovereign CDS spreads. The mean and median values of the adjusted R^2s are 66.1% and 70.1% respectively. Indeed some may argue that the adjusted R^2s are unusually high given that we are regressing changes in a dependent variable on changes in explanatory variables, thus effectively removing relevant long-run information from the data. To make sure that these R^2 are not spuriously high, we also include a linear time trend in the regressions. However, the resulting adjusted R^2s are only slightly reduced (by less than 1%) in these regressions.

Turning now to the local variables, the results in Table 6 indicate that the local economy has a strong influence on the sovereign credit risk. The coefficients on the variables representing the local stock markets are significant at the 5% level for six out of the eight countries, and all of their coefficient estimates have negative signs.

Accordingly, a poor performance in the local stock market is seen to contribute to an increased sovereign credit risk. The exchange rate is also an important explanatory variable, with coefficient estimates being significant at the 10% level for five countries. Similar to those of the local stock markets, the coefficient estimates of the exchange rates have the negative signs, indicating that an appreciation of the local currency against the US dollar would have a positive effect on the reduction of the sovereign credit risk.

The foreign reserve is equally important in explaining the changes of the sovereign CDS spreads. Half of the coefficient estimates of these variables are statistically significant at the 5% level. European countries have negative coefficient estimates for foreign reserves, while Asian countries have positive ones. On one hand, we note that the foreign reserves in the selected European countries, which are developed economies, are kept at a relatively low level for long term. An increase in their foreign reserves signals that they can better service their foreign debt obligations. This results in a decrease in their sovereign CDS spreads. On the other hand, for the emerging markets, we note a large-scale use as well as the sizable accumulation of foreign exchange reserves, especially in Asia. See Mohanty and Turner, 2006, and Pineau et al., 2006). As pointed out by Fukuda and Kon (2008), when these developing countries increase their foreign exchange reserves, the liquid debt and total debt in these countries will increase as well. They also provided cross-country empirical evidence of increased foreign exchange reserves leading to outstanding larger external debt. This inevitably has deepened investors' concerns about the state of the economies in these emerging markets. As a result, the foreign reserve exerts the opposite effects on sovereign credit spreads in Asian countries relative to European countries.

The ratios for the local variables range from 32.3% to 73.8%. As mentioned earlier, this ratio measures the maximum explanatory power in percent of the local variable in the regression. Of the eight local ratios, five are larger than 50%. The mean and median values are 55.7% and 60.6% respectively. So the explanatory power of the local variables varies significantly across countries. On average, the local variables can explain about 56% of the variation of the sovereign credit risk.

The regression results for the global financial market variables are equally striking. The most significant variables belong to the global stock market returns. For five of the eight selected countries, the coefficient estimates of the global stock market variables are significant at the 10% level. To be more precise, the coefficient estimates of the global stock market return have negative signs for all of the Asian countries, and positive signs for most of the European countries. This result suggests that interestingly the effects of the global stock markets on the sovereign credit risk work

in the opposite directions in these two regions.

For the other global variables, the coefficient estimates are statistically significant at the 10% level for only two or three countries. We also notice that the coefficient estimates of all of the investment-grade variables and the coefficient estimates of most of the high-yield variables have positive signs in the regression. One possible explanation for this result is that the increased spread gap between bonds with various credit qualities is reflective of the increased risks in the bond market which, in turns, leads to the increased sovereign credit risk.

The ratios for the global financial markets range from 34.0% to 71.1%, with mean and median values of 53.2% and 58.3% respectively. Therefore, compared with the local economy factors, the global financial markets have comparable effects on the sovereign credit risk.

The ratios for the global risk premiums range from 24.0% to 71.5%, with a mean value of 47.7% and a median value of 50.7%. Although not as powerful as the local economy and the global financial markets, there is also a strong association between the global risk premiums and the sovereign credit risk. That is, the equity risk premium is significant at the 5% level for France, Germany, and the Philippines; whereas the volatility risk premium is significant at the 5% level; for China, Korea, and the Philippines; lastly the treasury risk premium is significant at the 5% level for China and the Philippines.

We note that the signs of the coefficiemt estimates for volatility are positive for all of the Asian countries, and negative for most of the European countries. This is consistent with the findings of Sugihara (2010). They showed that the correlation coefficients between VRP and risk indicators such as CDS index and swap spread in Japan have the opposite signs to those of Europe and the U.S.

Finally, the results for the regional spreads show that, even after we control for the local and global variables in the regression, there remain strong associations between the sovereign credit spreads. However, the ratios for the regional sovereign spreads range only from 9% to 37.9%, and the mean and median values of the ratio are only 23.0% and 21.8%. The Asian spread is significant at the 5% level for all of the Asian countries as well as France, while the European spread is significant for most of the European countries. The significance of these regional spread variables may be viewed as reflecting the influence of the regional or global factors on the sovereign credit risk that are not readily captured by other existing explanatory variables in the regressions. One possible interpretation for this is that it is attributed to a liquidity factor that maybe at work here (See Longstaff et al., 2011). We notice again that the coefficient estimates for variables such as the foreign reserve, the global stock, and the volatility risk premium have the opposite signs for most of the European

countries compared with those for the Asian countries. This further highlights the importance of regional factors that may have been inadvertently excluded from the specification of our regressions.

Before proceeding to the next section, it is useful to briefly comment on the results reported in Table 6 in our study and those reported in Table 3 in the study conducted by Longstaff et al. (2011). There are notable differences between the two tables on the relative importance of some of the local and global variables in determining the sovereign credit default swap spreads, even for the same countries included in both studies, such as China, Japan, Korea and the Phillipines. The differences are in terms of statistical significance and/or implicitly expected sign for the coefficient estmates as reflected in the recorded sample t-statistics. We believe that the differences emanate largely from the fact that these two studies work with two slightly different sample periods (Longstaff et al. (2011) worked with a sample period from October 2000 to January 2010, while we work with a sample period from September 2004 to August to 2012). It is entirely possible, and in fact, to some extent, expected that associations between sovereign spreads and some of the variables used to proxy for the local and global factors have undergone important structural changes over time. Indeed, we can argue that the 2000-2010 period is rather unique in the sense that the global liquidity factors appeared to have exerted more prominent roles, and the country-specific factors less prominent roles, in determining the sovereign spreads of the selected Asian countries. Indeed, this very point has also been stressed in Longstaff et al. (2011). Motivated by this argument, we perform our subsequent analyses based on two subsamples characterized by pre and post-crisis regimes respectively, as it is well-known that negelected structural changes can impart considerable biases in the parameter estimates of the pricing model for sovereign CDS spreads to be discussed in the next section.

5   The Pricing Model

As mentioned by Pan and Singleton (2008), the basic pricing principle of sovereign CDS contracts is similar to that of corporate CDS contracts. Following this argument, we introduce a model to price sovereign CDS spreads in this section.

5.1 The Model

For a standard sovereign CDS contract with semi-annual premium payments, we have the following equation:

$$\frac{1}{2}CDS_t(M)\sum_{j=1}^{2M}E_t^{\mathbb{Q}}\big[e^{-\int_t^{t+.5j}(r_s+\lambda_s^{\mathbb{Q}})ds}\big] = (1-R^{\mathbb{Q}})\int_t^{t+M}E_t^{\mathbb{Q}}\big[\lambda_u^{\mathbb{Q}}e^{-\int_t^u(r_s+\lambda_s^{\mathbb{Q}})ds}\big]du, \quad (12)$$

where M is the maturity in years of the CDS contract; $CDS_t(M)$ is the annualized CDS spread at issue; r_t is the riskless rate; $R^{\mathbb{Q}}$ is the risk-neutral recovery rate of face value on the underlying cheapest to delivery bond in the event of a credit event; λ_t is the risk-neutral intensity of default, i.e. the intensity of arrival rate of a credit event. To fix notation, in this paper, the superscript $\mathbb{Q}$ is used to denote the parameters of relevant processes under the risk-neutral measure, and $\mathbb{P}$ is used for the process under the historical/physical measurre.

As explained by Pan and Singleton (2008), the left hand side of Equation (12) represents the present value of the contingent payment that the buyer of the CDS contracts needs to pay upon a credit event not having occurred; while the right hand side of the equation is the present value of the payoff the buyer receives from the contract seller upon a credit event. These values are discounted by $r_t + \lambda_t^{\mathbb{Q}}$ because of their survival-dependent nature. Assume that λ_t and r_t are statistically independent, the arbitrage-free price of a standard sovereign CDS contract with M years maturity at issue can be written as:

$$
\begin{aligned}
CDS_t(M) &= \frac{2(1-R^{\mathbb{Q}})\int_t^{t+M}E_t^{\mathbb{Q}}\big[\lambda_u^{\mathbb{Q}}e^{-\int_t^u(r_s+\lambda_s^{\mathbb{Q}})ds}\big]du}{\sum_{j=1}^{2M}E_t^{\mathbb{Q}}\big[e^{-\int_t^{t+.5j}(r_s+\lambda_s^{\mathbb{Q}})ds}\big]} \\
&= \frac{2(1-R^{\mathbb{Q}})\int_t^{t+M}D(t,u)E_t^{\mathbb{Q}}\big[\lambda_u^{\mathbb{Q}}e^{-\int_t^u\lambda_s^{\mathbb{Q}}ds}\big]du}{\sum_{j=1}^{2M}D(t,t+j/2)E_t^{\mathbb{Q}}\big[e^{-\int_t^{t+.5j}\lambda_s^{\mathbb{Q}}ds}\big]},
\end{aligned}
\qquad (13)
$$

where $D(t,u)$ refers to the price of a default-free zero-coupon bond issued at date t and maturing at date u.

Given the recovery rate $R^{\mathbb{Q}}$, we define the loss rate as $L^{\mathbb{Q}} = (1 - R^{\mathbb{Q}})$. Based on the discussions in Pan and Singleton (2008), it is appropriate to treat $L^{\mathbb{Q}}$ as a constant parameter,[13] and assume that there is no risk premium on recovery, namely $L^{\mathbb{Q}} = L^{\mathbb{P}}$.

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[13]The academic literature tends to treat this lost rate as a constant parameter. In practice, traders usually set $L^{\mathbb{Q}} = 0.75$. Actually whether or not this $L^{\mathbb{Q}}$ is consistent with the historical distribution of the real loss rate is not be material for pricing new issued CDS contracts (see Pan and Singleton, 2008).

Turning now to the risk-neutral intensity of a credit event $\lambda^{\mathbb{Q}}$, the literature usually assumes that $\lambda_u^{\mathbb{Q}}$ follows one of the following three models: a CIR square-root diffusion model (Zhang, 2003; Longstaff et al., 2005); a "three-halves" diffusion model (Ahn and Gao, 1999); or $ln(\lambda^{\mathbb{Q}})$ following an Ornstein-Uhlenbeck process (Berndt et al., 2008; Pan and Singleton, 2008; Longstaff et al., 2011).

In this paper, we use the CIR model for the following reasons. First, the CIR model assures $L^{\mathbb{Q}}$ to be non-negative and mean-reverting. Second, using the CIR model enables us to obtain closed-form solutions for the expectations in the numerator and denominator of Equation (13). This greatly simplifies the optimization problem as well as the required computational steps.

Specifically, $\lambda^{\mathbb{Q}}$ is assumed to follow a CIR model under the physical measure $\mathbb{P}$:

$$d\lambda_t^{\mathbb{Q}} = \kappa^{\mathbb{P}}(\theta^{\mathbb{P}} - \lambda_t^{\mathbb{Q}})dt + \sigma_\lambda\sqrt{\lambda_t^{\mathbb{Q}}}dB_t^{\mathbb{P}}, \tag{14}$$

as well as under the risk-neutral measure $\mathbb{Q}$:

$$d\lambda_t^{\mathbb{Q}} = \kappa^{\mathbb{Q}}(\theta^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})dt + \sigma_\lambda\sqrt{\lambda_t^{\mathbb{Q}}}dB_t^{\mathbb{Q}}. \tag{15}$$

The market price of risk, η_t, that connects these two processes underlying the change of measure from $\mathbb{P}$ to $\mathbb{Q}$ is defined as:

$$\eta_t = \frac{\delta_0 + \delta_1\lambda_t^{\mathbb{Q}}}{\sqrt{\lambda_t^{\mathbb{Q}}}}, \tag{16}$$

where $\kappa^{\mathbb{P}} = \kappa^{\mathbb{Q}} - \delta_1\sigma_\lambda$ and $\kappa^{\mathbb{P}}\theta^{\mathbb{P}} = \kappa^{\mathbb{Q}}\theta^{\mathbb{Q}} + \delta_0\sigma_\lambda$.

Based on the CIR model, we can calculate the following elements:

$$E_t\left[\exp\left(\beta\int_t^s \lambda_u du\right)\right] = A(\beta, \tau)e^{B(\beta,\tau)\lambda_t}, \tag{17}$$

$$E_t\left[\lambda_s \exp\left(\beta\int_t^s \lambda_u du\right)\right] = \left[C(\beta, \tau) + D(\beta, \tau)\lambda_t\right]e^{B(\beta,\tau)\lambda_t}, \tag{18}$$

for any β, where $\tau = s - t$ and

$$\phi = \sqrt{-2\beta\sigma^2 + \kappa^2}, \tag{19}$$

$$\gamma = \frac{\kappa + \phi}{\kappa - \phi}, \tag{20}$$

$$A(\beta, \tau) = \exp\left(\frac{\kappa\theta(\phi + \kappa)}{\sigma^2}\tau\right)\left(\frac{1 - \gamma}{1 - \gamma e^{\phi\tau}}\right)^{\frac{2\kappa\theta}{\sigma^2}}, \tag{21}$$

$$B(\beta, \tau) = \frac{\kappa - \phi}{\sigma^2} + \frac{2\phi}{\sigma^2(1 - \gamma e^{\phi\tau})}, \tag{22}$$

$$C(\beta, \tau) = \frac{\kappa\theta}{\phi}(e^{\phi\tau} - 1)\exp\left(\frac{\kappa\theta(\phi + \kappa)}{\sigma^2}\tau\right)\left(\frac{1 - \gamma}{1 - \gamma e^{\phi\tau}}\right)^{\frac{2\kappa\theta}{\sigma^2} + 1}, \tag{23}$$

$$D(\beta, \tau) = \exp\left(\frac{\kappa\theta(\phi + \kappa) + \phi\sigma^2}{\sigma^2}\tau\right)\left(\frac{1 - \gamma}{1 - \gamma e^{\phi\tau}}\right)^{\frac{2\kappa\theta}{\sigma^2} + 2}. \tag{24}$$

where given Equation (13), we can set $\beta = 1$ for the purpose of calculating these expectations.

5.2 Maximum Likelihood Estimation

In this section, we apply the pricing model in subsection 5.1 to sovereign CDS spreads and estimate the parameters in the model by using a the method of maximum likelihood (ML). As mentioned in Longstaff et al. (2011), to estimate the parameters, we need to construct a term structure of CDS spreads for each sovereign in ours study.

For this purpose, we collect one-year and three-year sovereign CDS data for selected countries from September 2004 to December 2011.[14] Now for these countries, we have a term structure of one-year, three-year, and five-year sovereign CDS contracts. Similar to Longstaff et al. (2011), parameters are estimated by the ML method based on the conditional distribution of the observed spreads implied by the non-central chi-square distribution of λ.

We also assume that there is no pricing error for the three-year contract, while the one-year and five-year contracts have pricing errors, which follow a normal distribution with mean zero and standard deviation given by $\sigma_\varepsilon(1)$ and $\sigma_\varepsilon(5)$ respectively.[15] Longstaff et al. (2011) built a term structure of one-year, two-year, three-year, five-year, seven-year, and ten-year CDS contracts, and assumed zero pricing errors for

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[14]The time period is shrunk because sovereign CDS data are not available for several countries after December 2011.

[15]The MLE of model parameters relies on the term structure of sovereign CDS data. Constrained by data availability, we only obtain one-year, three-year, and five-year sovereign CDS data from the Bloomberg data base. We assume that the three-year contract has no pricing error.

the five-year contracts. They found that based on stated assumption and CDS term structure, the pricing error $\sigma_\varepsilon(M)$ "tend to be smaller for the intermediate maturities." Besides, as discussed earlier, the recovery rate $R^{\mathbb{Q}}$ is set to be 0.25. The present value of default-free zero-coupon bonds $D(t, u)$ is boostrapped from the Constant Maturity Treasury (CMT) yield using a standard cubic spline interpolation method.

Specifically, for the estimation of the CIR process by ML, we provide the following details. Consider a CIR process

$$d\lambda_t = \kappa(\theta - \lambda_t)dt + \sigma\sqrt{\lambda_t}dB_t, \tag{25}$$

where, if κ, θ, σ are all positive, and $2\kappa\theta > \sigma^2$ holds, this process has a steady marginal distribution. Given λ_t at time t, the density of $\lambda_{t+\Delta t}$ is

$$p(\lambda_{t+\Delta t}|\lambda_t; \kappa, \theta, \sigma, \Delta t) = ce^{-u-v}(\frac{v}{u})^{\frac{q}{2}}I_q(2\sqrt{uv}), \tag{26}$$

where

$$c = \frac{2\kappa}{\sigma^2(1 - e^{-\kappa\Delta t})}), \tag{27}$$

$$u = c\lambda_t e^{-\kappa\Delta t}, \tag{28}$$

$$v = c\lambda_{t+\Delta t}, \tag{29}$$

$$q = \frac{2\kappa\theta}{\sigma^2} - 1, \tag{30}$$

and $I_q(2\sqrt{uv})$ is a modified Bessel function of the first kind of order q.

The ML estimation of the parameters of the model is carried out on the time series of λ_t with N observations $\{\lambda_t, i = 1....N\}$. Note that N=88, namely 88 monthly observations from September 2004 to December 2011, and $\Delta t = \frac{1}{12}$, namely one month, in our case. The log-likelihood function of the CIR process is

$$
\begin{aligned}
\ln L(\kappa, \theta, \sigma) &= \sum_{i=1}^{N-1} \ln p(\lambda_{t+\Delta t}|\lambda_t; \kappa, \theta, \sigma, \Delta t) \\
&= (N-1)\ln c + \\
&\quad \sum_{i=1}^{N-1}\left[-u_{t_i} - v_{t_{i+1}} + 0.5qln(\frac{v_{t_{i+1}}}{-u_{t_i}}) + \ln(I_q(2\sqrt{v_{t_{i+1}}u_{t_i}}))\right]. \tag{31}
\end{aligned}
$$

By maximizing the log-likelihood function, namely Equation (31), we can obtain the ML Estimates (MLEs) of the parameters of the model as $\hat{\kappa}$, $\hat{\theta}$, and $\hat{\sigma}$; that is, we

solve the following optimization problem:

$$
\begin{aligned}
(\hat{\kappa}, \hat{\theta}, \hat{\sigma}) &= \arg \max_{(\kappa, \theta, \sigma)} \ln L(\kappa, \theta, \sigma) \\
&= \arg \min_{(\kappa, \theta, \sigma)} \big\{ - \ln L(\kappa, \theta, \sigma) \big\},
\end{aligned}
\tag{32}
$$

by using the *fminsearch* function in MATLAB, which is an implementation of Nelder-Mead simplex method. For the evaluation of the modified Bessel function of the first kind $I_q(2\sqrt{vu})$, we used a scaled version of the Bessel function in MATLAB with the command *besseli*$(q, 2\sqrt{uv}, 1)$, since the original Bessel function approaches rapidly to the $+\infty$ and optimization function *fiminsearch* is not able to handle this.

5.3   Empirical Results

Before the ML method is used to estimate the parameters of our pricing model and price the sovereign CDS spreads, we introduce a test for the model estimation process.

First, we assign certain initial values to the parameters of the model. Second, we simulate the default intensity λ for the same length of the sample period[16] using a Monte Carlo method. Then, we obtain the model-implied spreads for one-year, three-year, and five-year CDS contracts, and add the normally distributed pricing errors to the spreads of one-year and five-year contracts. Finally, using these simulated CDS spreads, we can estimate the underlying parameters via the ML method. This simulation and estimation test process is repeated 100 times, so that we can calculate the mean and standard deviation of the pricing errors.

The test results are reported in Table 7. The average value of the total pricing error for the simulated data is only 0.2813% with a standard deviation value of 0.0175%. This leads us to conclude that the sovereign credit model with our ML estimated parameters of the model is able to price the data accurately. We notice that the model prices the three-year contracts perfectly with a zero pricing error. For the five-year data, the average value of the pricing error is only 0.1567%, which is still quite accurate. However, for the one-year contracts, the average value of the pricing error can be as large as 1%, much higher than that of the five-year contracts. Thus, there are drawbacks associated with the term structure of contracts in this pricing model, especially when the model is used to price the one-year contracts.

---

[16]In this section, the sample period is set to be from September 2004 to December 2011, which covers 88 months. So, the number of simulation timesteps is 88. The length of the simulation timestep is one month, and the number of simulation trajectories is 100,000.

	Mean	Standard Deviation
Log-likelihood	21.20	0.4085
Total Pricing Error	0.2813%	0.0175%
Pricing Error for 1-year CDS	0.9978%	0.0807%
Pricing Error for 3-year CDS	0.0000%	0.0000%
Pricing Error for 5-year CDS	0.1567%	0.0131%

[1] The simulation is conducted under the initial parameter values with 100,000 trajectories for 88 months. The mean and standard deviation are calculated with 100 simulation runs. The initial values of underlying parameters are: $\kappa^{\mathbb{Q}} = 0.045$, $\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}} = 0.022$, $\sigma_\lambda = 0.028$, $\kappa^{\mathbb{P}} = 0.55$, $\kappa^{\mathbb{P}}\theta^{\mathbb{P}} = 0.055$.

5.4 Full Sample Results

The above test shows that the ML method can be used to evaluate the data reasonably accurately with the CIR model. So in this part, we adopt it to the real data for the full sample. Our focus is on a subset of sovereigns, which include China, Germany, Italy, Korea, and the Philippines. France, Japan, and Spain are excluded from the data set because there are not enough sovereign CDS term structure data available for the purpose of estimation. As mentioned earlier, the sample period is set to be from September 2004 to December 2011 for the five countries due to data availability.

Table 8 reports the ML estinated parameters of our sovereign credit risk model. First, for the total pricing error of the model, we see that China, Italy, and Korea have relatively moderate pricing errors. However, for other countries, especially for Germany and the Philippines, there are large gaps between the true CDS spreads and the model prices. The average pricing error is 18.36%, and the median value is 16.40%.

We now turn to the respective pricing errors for one-year, three-year, and five-year CDS contracts. There are no pricing errors for all of the three-year contracts of all of the countries. This is because we have assumed that the three-year contracts can be priced perfectly using the model, and it is based on this assumption that we build the estimation on the term-structure of sovereign CDS. For the five-year contracts, the pricing errors range from 10.71% to 35.96%, with an average value of 20.34% and a median value of 18.36%. For the one-year contracts, the pricing errors range from 16.00% to 73.89%, with an average value of 42.03% and a median value of 36.77%.

Table 8: MLEs of Parameters of Sovereign Credit Risk Model[1]

|	China	Germany	Italy	Korea	Philippines	Mean	SD	Median
$\kappa^{\mathbb{Q}}$	0.0014	0.0305	0.0214	0.0011	0.0002	0.0109	0.0141	0.0014
$\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$	5.39E-4	4.83E-5	2.56E-4	8.10E-4	8.81E-4	5.07E-4	3.56E-4	5.39E-4
σ_{λ}	0.0757	0.2666	0.1182	0.0868	0.0952	0.1285	0.0787	0.0952
$\kappa^{\mathbb{P}}$	0.4441	0.6960	2.4723	0.2006	0.2000	0.8026	0.9557	0.4441
$\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$	0.0029	0.0355	0.0070	0.0038	0.0045	0.0107	0.0139	0.0045
$\sigma_{\varepsilon}(1)$	0.0017	0.0013	0.0030	0.0015	0.0077	0.0030	0.0027	0.0017
$\sigma_{\varepsilon}(5)$	0.0016	0.0013	0.0016	0.0014	0.0064	0.0025	0.0022	0.0016
Log-likelihood	15.22	14.81	14.37	14.37	10.89	13.93	1.74	14.37
Total Pricing Error(%)[2]	16.40	31.81	12.31	8.55	22.72	18.36	9.17	16.40
Pricing Error for 1-year CDS(%)	36.77	73.89	27.22	16.00	56.27	42.03	23.14	36.77
Pricing Error for 3-year CDS(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pricing Error for 5-year CDS(%)	18.36	35.96	12.65	10.71	24.03	20.34	10.16	18.36

[1] The sample data are monthly sovereign CDS spreads for the period from Sept 2004 to Dec 2011.

[2] All of the pricing error in percentage mentioned in this table are calculated as the absolute differences between model price and market price over the market price.

For each row of the absolute pricing errors in percentage, we see that the ranking of the five countries is consistent. That is, Korea has the smallest pricing error in percent, while Germany has the largest. For each column, i.e., for each sovereign, the percent error for the one-year contract is always much larger than the percent error for the five-year contract.

Based on the observation on the pricing errors, we draw the following two conclusions. First, the pricing error for one-year contracts is always bigger than the pricing error for five-year contracts, while the three-year contracts are priced perfectly. This conclusion is consistent with the findings of Pan and Singleton (2008), where they found that the one-year contracts were the least well priced by the one-factor model. They reported that some "components of the short ends of the CDS curves" are not well captured by the one-factor model. This can be explained by the idiosyncratic liquidity factor caused by the sizable transactions of the short-dated CDS contracts, since large financial institutions tend to use these contracts as "primary vehicles to express views on sovereign bonds."

Second, the accuracy of our sovereign credit risk model varies greatly from country to country. Among all of these countries, Germany has the largest pricing error, 31.81%. Recall that in our regression analyses, the adjusted R^2 of Germany is only 15.3%, which is much less than that for the other countries. That is, when the variance in the CDS spreads of most of the countries can be largely captured by some common explanatory variables, the variance of Germany captured by the same variables is limited to some extent. It seems that a large part of the components of Germany's CDS curves are not captured by the one-factor model. Multiple factors may have to be introduced into the model in order to increase its pricing accuracy

Percentage Difference between Model Price and Market Price
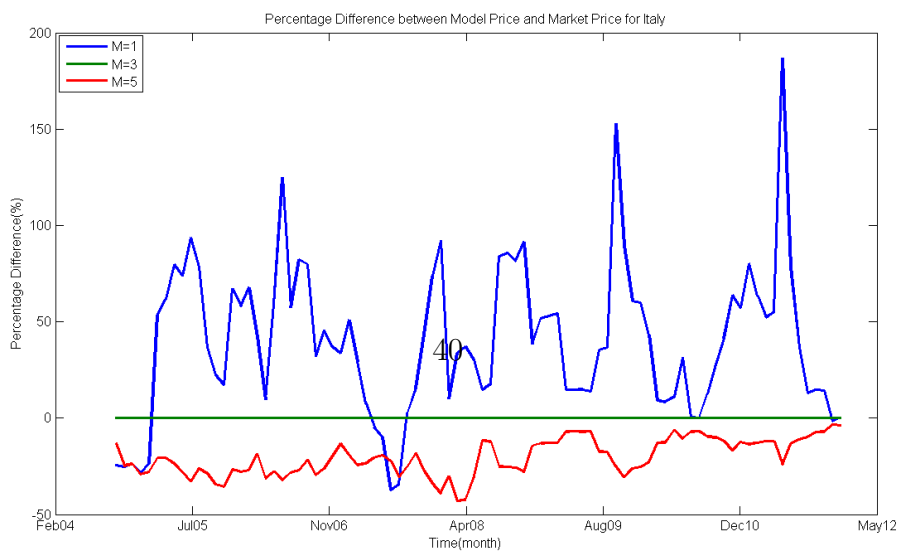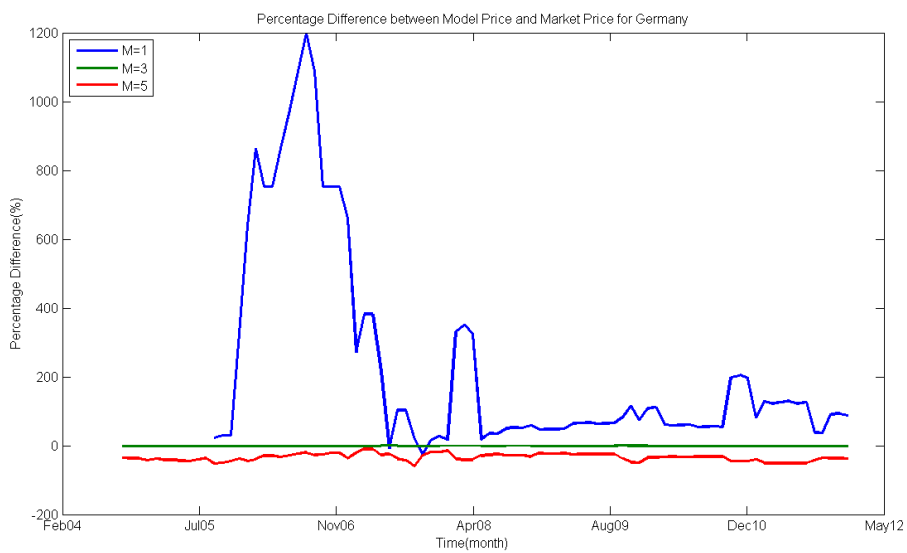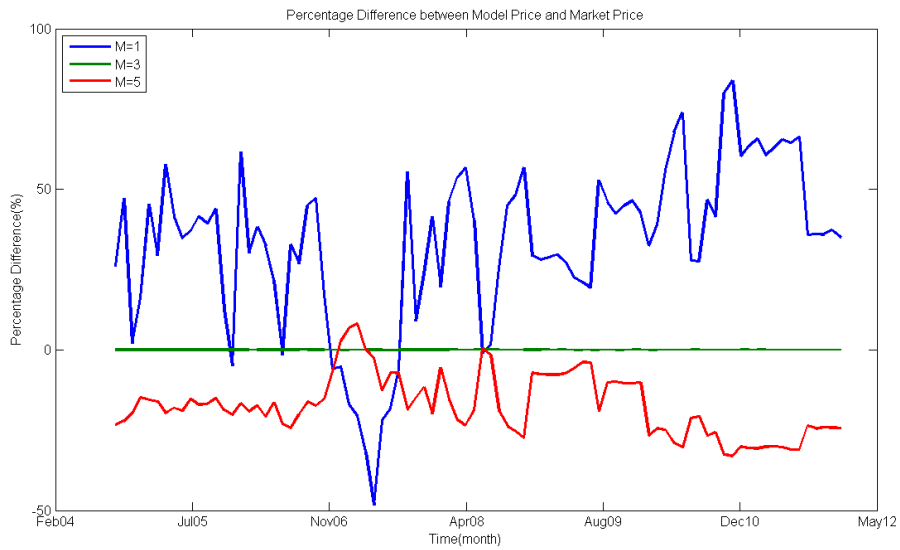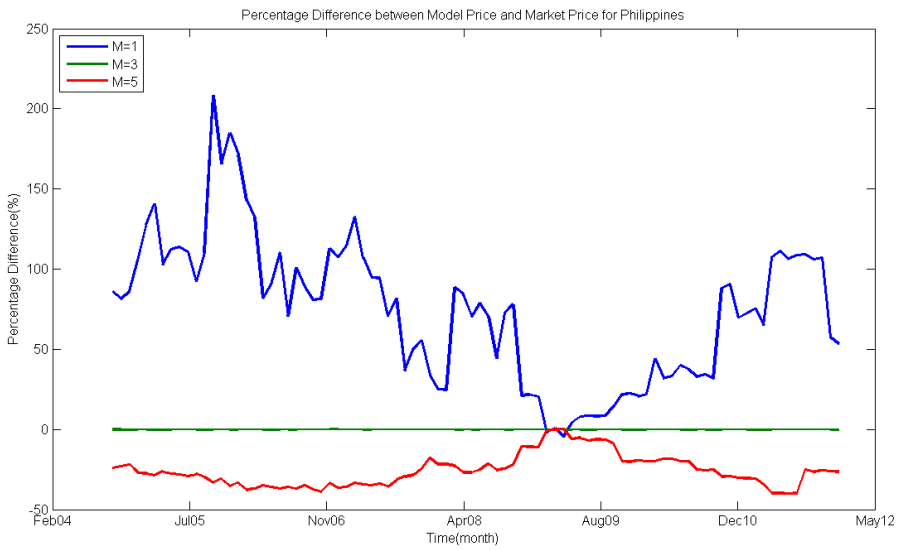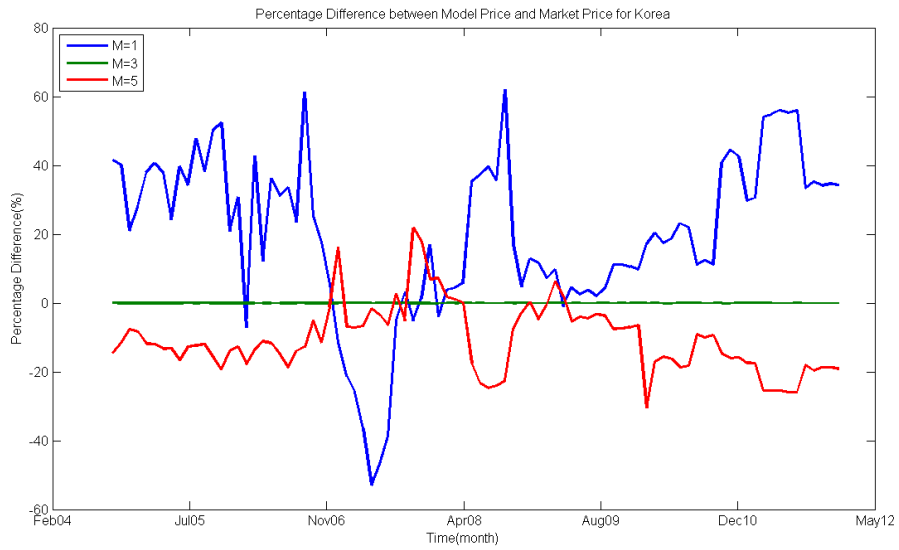
Figure 6: Percentage Difference between Model Price and Market Price

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for Germany.

These pricing errors in percentage, as reported in Table 8, are calculated in the absolute value term. Next, we consider the real values of the pricing error in percentage,[17] which are plotted in Figure 6 for the five sovereigns respectively. As we can see from this figure, the three-year contracts are priced perfectly, which can be used as a benchmark.

As shown, most of the times, for all of the sovereigns considered in our study, the model prices for one-year contracts are overestimated, while the model prices for five-year contracts are underestimated. This finding is consistent with the results of Pan and Singleton (2008) and Longstaff et al. (2011). We argue that this is due to the drawbacks of our one-factor credit risk model based on the CDS term structure. Meanwhile, the region of the pricing errors for one-year contracts is evidently larger than that for five-year contracts, consistent with the results of the pricing errors reported in Table 8. According to Pan and Singleton (2008), a possible explanation for this anomalous behavior of one-year contract is "the liquidity or supply/demand premium."[18]

There are also other interesting findings for the estimates of the model's parameters. For instance, values of $\sigma_\varepsilon(1)$ are no less than values of $\sigma_\varepsilon(5)$ for all of the sovereigns considered in this paper. As discussed earlier, the short ends of the CDS curves are less well captured by our one-factor model compared with the five-year contracts. As a result, we expect to see increased volatility in the model pricing error ε for a one-year contract.
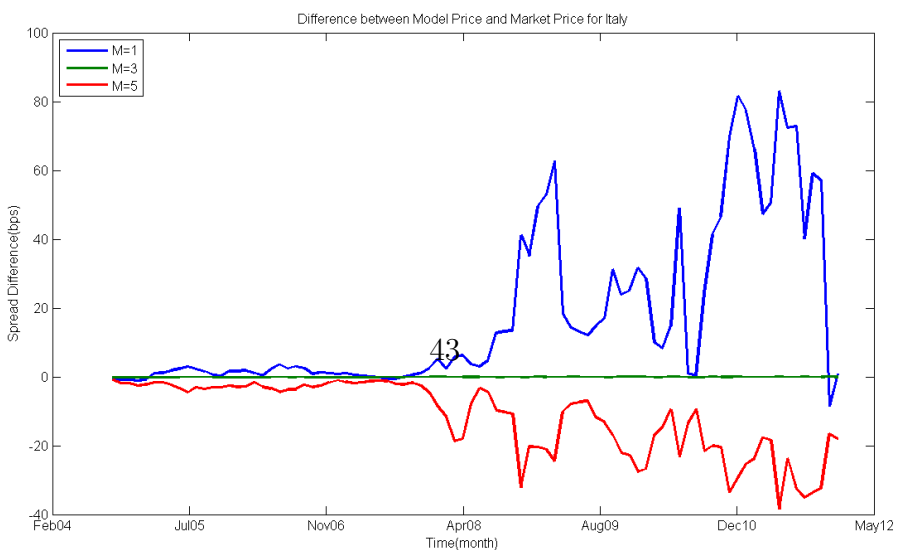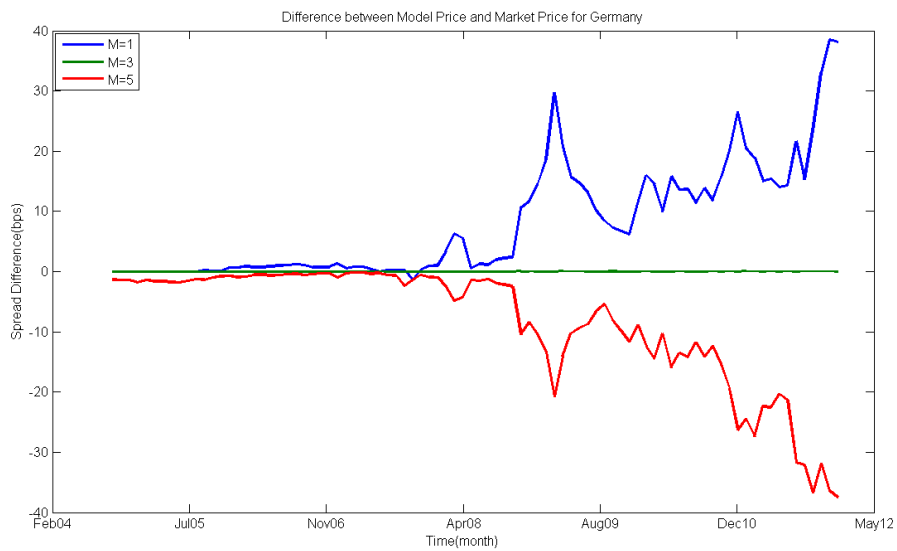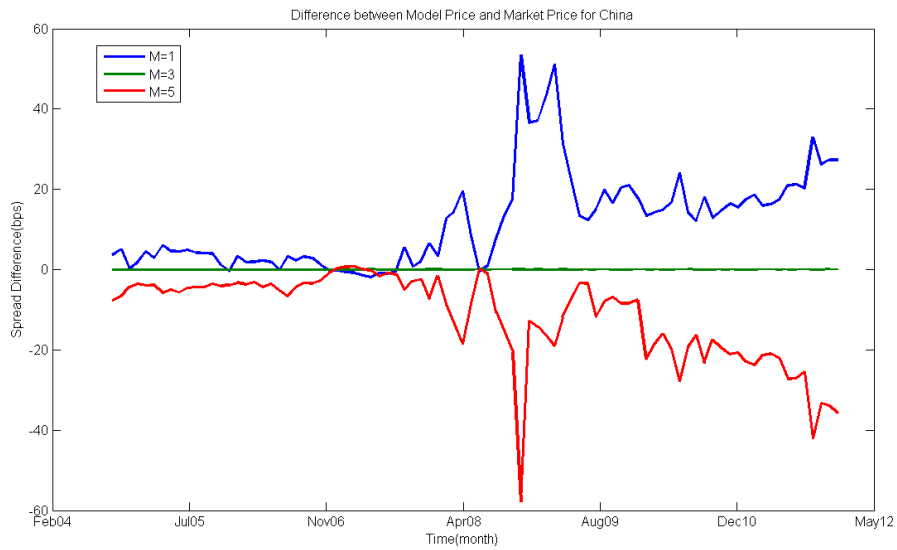
The median values for them are 17 and 16 basis points respectively. Similar to the conclusions reached by Longstaff et al. (2011), this volatility is acceptable from a percentage perspective, considering that the sovereign spreads can go up to hundreds of basis points in Table 2.
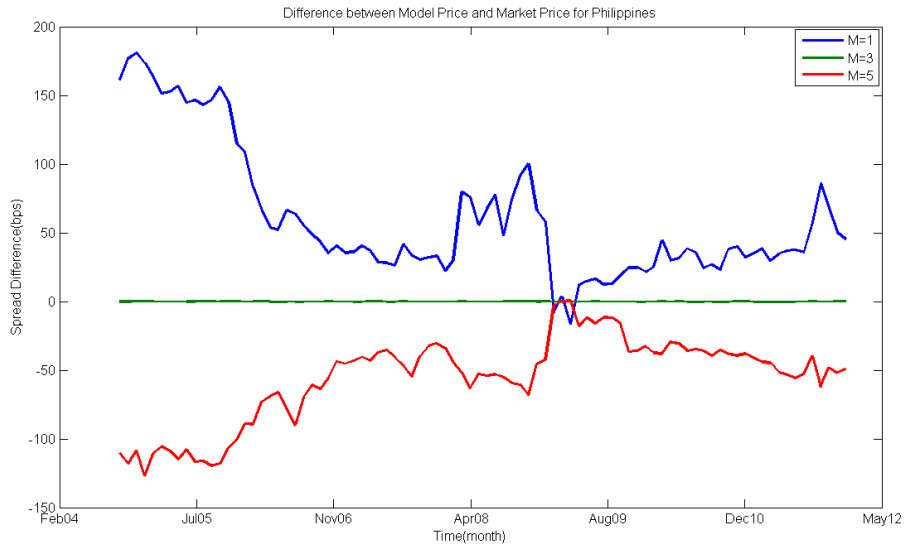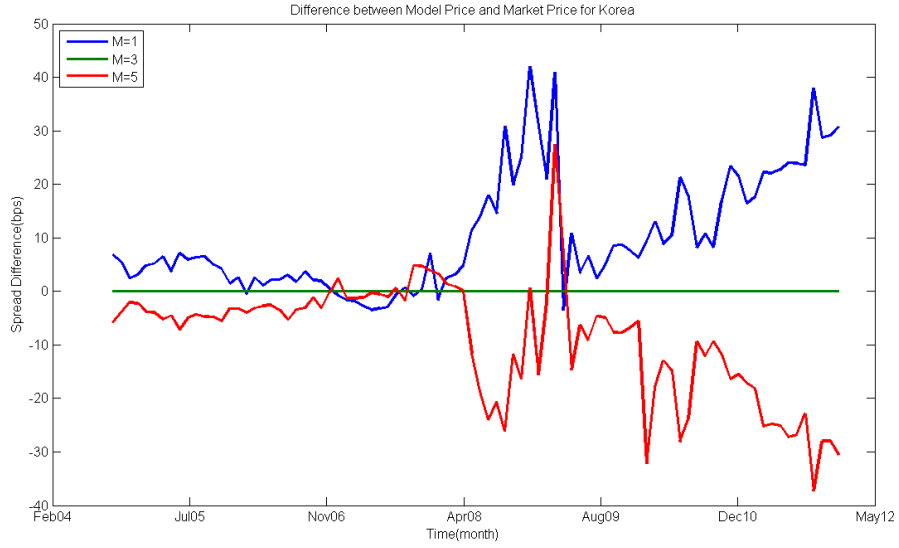
Finally, we plot the difference between the model price and the market price in basis points in Figure 7. Similarly, the difference for three-year contracts are zero and can be regarded as a benchmark. The tendency for underestimation for five-year contracts and the tendency for overestimation for one-year contracts are also visible in this case. Another noticeable feature is that, except for the Philippines, there are only minor differences around zero in basis points between the model price and the market price for other sovereigns before April 2008. But these differences appear to

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[17]For each month, the numerator is calculated by subtracting market price from model price, and the denominator is the market price

[18]Because large financial institutions tend to use the one-year CDS contracts as a 'trading vehicle for expressing view on sovereign bonds," which results in an "idiosyncratic liquidity factor" to the performance of one-year contracts.

Difference between Model Price and Market Price for China

Difference between Model Price and Market Price for Germany

Difference between Model Price and Market Price for Italy

Figure 7: Difference between Model Price and Market Price

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have widened since then.

The above results lead us to conclude that the 2008-2009 financial crisis appears to have induced important structural changes in our credit risk model. Before the financial crisis, the performance of the model is reasonably ideal. This contrast reminds us of the PCA results presented in Table 5, where we also noticed a large difference between the results before and after the financial crisis. Based on all of the results obtained so far, it would be inappropriate to base our analysis on the estimates of the parameters of the model obtained from the full sample.

After the 2008-2009 financial crisis and the Euro debt crisis, there is a large increase in the arrival rate $\lambda^{\mathbb{Q}}$ for credit events. Accordingly, in order to improve the performance of our pricing model, we estimate these parameters from the model for the pre-crisis and post-crisis periods separately.

5.5   Pre and Post-Crisis Results

In this subsection, we divide the sample into a pre-crisis period, which covers the period from September 2004 to August 2008, and a post-crisis period, which covers the period from September 2008 to December 2011. Then we use the ML method to estimate the parameters of the model for each period separately. The absolute pricing errors in percentage using the ML method for the two subsamples (the percentage is calculated based on the data for the full sample period) are reported in Table 9. The resulting estimation results are reported in Table 10.

Table 9: Total Absolute Pricing Errors in Percentage

	China	Germany	Italy	Korea	Philippines	Mean	SD	Median
Total Pricing Error(%)	13.81	20.07	8.13	9.23	16.14	13.47	4.41	13.81
Pricing Error for 1-year CDS(%)	31.01	50.41	19.69	17.17	40.47	31.75	12.51	31.01
Pricing Error for 3-year CDS(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pricing Error for 5-year CDS(%)	15.44	20.93	7.14	11.62	16.83	14.39	4.69	15.44

Compared with the results in Table 8, the total absolute pricing errors in Table 9 based on the estimates of the parameters of the model for the two subsamples are substantially reduced. The mean of the total pricing error is reduced from the previous value of 18.36% to the value of 13.47%, with a smaller standard error and a smaller median as well. Now, the total pricing errors in percentage range from 8.13% to 20.07%, which are acceptable considering the shortcomings of the one-factor model. In addition, most of the pricing errors in percentage for one-year and five-year contracts decrease as well. Thus, we conclude that using the MLEs of the parameters of the model from subsamples improves the performance of our credit risk pricing model considerably.

Table 10: MLEs of Parameters of the Model for Pre-crisis and Post-crisis Periods

Time Period	Parameters	China	Germany	Italy	Korea	Philippines	Mean	SD	Median
	$\kappa^{\mathbb{Q}}$	0.0022	0.0322	0.0002	0.0017	0.0034	0.0079	0.0122	0.0022
	$\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$	5.39E-4	7.22E-5	1.64E-14	8.09E-4	5.77E-3	1.44E-3	2.19E-3	5.39E-4
	σ_{λ}	0.0570	1.0405	0.2717	0.0682	0.1042	0.3083	0.3741	0.1042
	$\kappa^{\mathbb{P}}$	0.5750	1.6088	2.6279	0.2672	0.2451	1.0648	0.9260	0.5750
Sept 2004 - Aug 2008	$\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$	0.0016	0.5413	0.2320	0.0023	0.0054	0.1565	0.2118	0.0054
	$\sigma_{\varepsilon}(1)$	0.0005	0.0004	0.0005	0.0007	0.0071	0.0018	0.0026	0.0005
	$\sigma_{\varepsilon}(5)$	0.0006	0.0002	0.0008	0.0007	0.0051	0.0015	0.0018	0.0007
	Log-likelihood	18.07	16.56	6.53	17.28	11.7	14.03	4.36	16.56
	Abs Pricing Error(%)	13.39	67.30	37.81	10.98	17.57	29.41	21.18	17.57
	$\kappa^{\mathbb{Q}}$	0.0002	0.0002	0.0003	0.0002	0.0002	0.0002	0.0001	0.0002
	$\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$	1.07E-3	5.98E-4	2.70E-3	6.35E-4	7.20E-4	1.14E-3	7.94E-4	7.20E-4
	σ_{λ}	0.0734	0.0786	0.1259	0.1076	0.1047	0.098	0.0195	0.1047
	$\kappa^{\mathbb{P}}$	0.2000	0.2000	1.0015	0.2025	0.2113	0.3631	0.3193	0.2025
Sept 2009 - Dec 2011	$\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$	0.0027	0.0055	0.0094	0.0058	0.0055	0.0058	0.0021	0.0055
	$\sigma_{\varepsilon}(1)$	0.0020	0.0010	0.0029	0.0022	0.0044	0.0025	0.0011	0.0022
	$\sigma_{\varepsilon}(5)$	0.0019	0.0011	0.0008	0.0021	0.0041	0.0020	0.0012	0.0019
	Log-likelihood	13.85	15.83	13.75	12.38	11.44	13.45	1.49	13.75
	Abs Pricing Error(%)	13.93	16.37	6.06	8.81	14.44	11.92	3.85	13.93

Turning now to the estimates of the parameters of the model in Table 10, we see substantially different magnitudes of the estimates of the parameters of the model before and after the crisis. For example, the pricing errors $\sigma_\varepsilon(1)$ and $\sigma_\varepsilon(5)$ tend to differ from zero much more frequently in the post-crisis period than in the pre-crisis period. The median values of $\sigma_\varepsilon(1)$ and $\sigma_\varepsilon(5)$ are 5 and 7 basis points respectively in the pre-crisis period; while those values increase to 22 and 19 basis points in the post-crisis period. This is consistent with the contrast of the general low levels of sovereign CDS spreads with the high ones before and after the 2008-2009 financial crisis. This reflects the fact that the CDS data show substantially more temporal variations in the post-crisis period.

In addition, we also notice that the absolute pricing errors are reduced to a larger extent after the crisis. This indicates that our pricing model provides a better fit to the sovereign CDS market data after the crisis. We do not wish to further elaborate on the comparison of κ, $\kappa\theta$, and σ_λ under the historical and risk-neutral distributions, except to say that the estimates of these parameters vary widely from country to country before the crisis. However, their ranges decrease to a smaller scale after the crisis.

To summarize, the estimation from the pre and post-crisis periods leads to more reasonable estimates of the parameters of our picing model. This gives us a more accurate pricing of the sovereign's CDS spreads.

6 Components of CDS Spreads

Following Pan and Singleton (2008) and Longstaff et al. (2011), we now analyze and decompose the sovereign credit risk into distress risk premium and credit-event components.

6.1 Decomposition of Sovereign Credit Risk

The different values of the parameters that describe $\lambda^{\mathbb{Q}}$ under the historical and the risk-neutral distributions indicate that there is systematic risks related to changes of measure, since future intensity of credit events, will change from "consensus expectations" in the CDS market (Pan and Singleton, 2008). For bearing this risk with a higher default (or other credit events) probability, investors will ask for a compensation, which is the distress risk premium.

As discussed earlier, sovereign credit risk can be decomposed into two components: risk premium components and credit-event components. The former represents the compensation for bearing the systematic risks, while the latter represents

the compensation for bearing the possibility of credit events implied by the historical distribution.

Following Pan and Singleton (2008), given the arrival rates of credit events and its governing parameters under the historical/physical measure $\mathbb{P}$, we calculate the credit-event components as:

$$CDS_t^{\mathbb{P}}(M) = \frac{2(1-R^{\mathbb{Q}})\int_t^{t+M} D(t,u)E_t^{\mathbb{P}}\left[\lambda_u^{\mathbb{Q}}e^{-\int_t^u \lambda_s^{\mathbb{Q}}ds}\right]du}{\sum_{j=1}^{2M} D(t,t+j/2)E_t^{\mathbb{P}}\left[e^{-\int_t^{t+.5j}\lambda_s^{\mathbb{Q}}ds}\right]}. \tag{33}$$

and the risk premium components can be calculated as the difference between the model spreads and the credit-event spreads:

$$RP(\text{Risk Premium}) = CDS_t(M) - CDS_t^{\mathbb{P}}(M). \tag{34}$$

Based on Equations (33) and (34), we can also evaluate the fractional influences or weights of risk premium components in total CDS spreads as:

$$WRP(\text{Weights of Risk Premium}) = \frac{CDS_t(M) - CDS_t^{\mathbb{P}}(M)}{CDS_t(M)}. \tag{35}$$

6.2 Risk Premium Analyses

Based on the estimated parameters of the model,[19] we calculate the risk premium and credit-event components for five-year sovereign CDS contracts[20]. Table 11 presents descriptive statistics for the risk premium components and the weights of the risk premium components embedded in the five-year sovereign CDS contracts. From this table, we see differences in the risk premium components between different sovereigns. We observe that the risk premium components for European countries are not consistent with our prior expectation. One possible explanation for this phenomenon is the sharp contrasts of the "safe" economic environment in the pre-crisis period with the great likelihood for systematic risks in the post-crisis period for European countries. The Euro debt crisis further aggravates the state of the economy and, in the process, intensifies the global concerns.

Figure 8 plots the decomposition of the five-year sovereign CDS contracts below. For each sovereign, the market price, the model price, the risk premium components, and the credit-event components are shown using different colors for each country.

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[19]Here, we use the estimates of the parameters of the model from subsamples reported in Table 10, because our model provides a more accurate pricing based on these estimates.

[20]We return to the five-year contracts in this section to consider the liquidity factor.

Table 11: Descriptive Statistics for Risk Premiums and Weights of Risk Premiums

Country	Risk Premiums (bps)			Weights of Risk Premiums (%)		
	Mean	Standard Deviation	Median	Mean	Standard Deviation	Median
China	6.06	12.95	1.13	6.1047	19.3308	4.4694
Germany	-1076.08	938.33	-1926.99	-80943.5235	90662.0141	-47820.0147
Italy	-287.05	358.47	-595.44	-6458.6955	7280.3237	-2724.1669
Korea	-11.53	28.11	-11.38	-32.3481	29.8537	-35.561
Philippines	41.34	53.87	46.45	14.4287	27.3187	33.8707

First, for all of the five countries, the market price line and the model price line match with each other, implying that our model prices the sovereign credit risk relatively well.
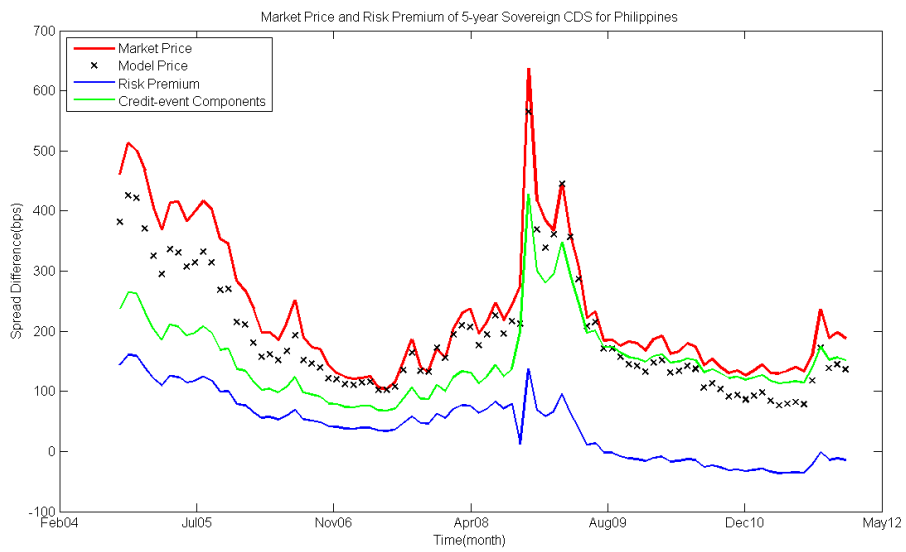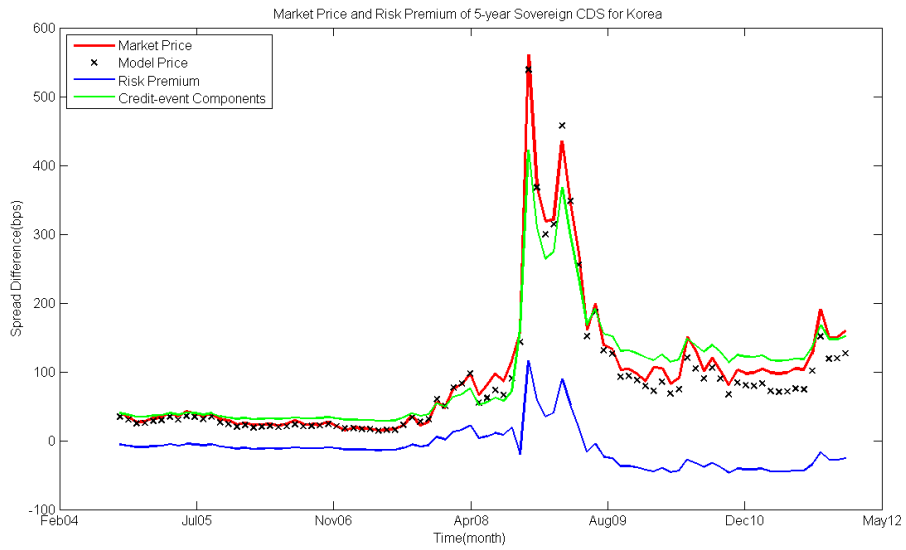
Second, the distributions of the CDS spreads and the components for Asian countries vary greatly compared with those for European countries. As shown in the table, for Asian countries, all of these components and prices remain at a relative low level before the 2008-2009 financial crisis,[21] and reach the peak during the crisis period. Comparing their risk premiums with their credit-event components, apparently the credit-event components play a vital role in the CDS markets, especially in the post-crisis period. As emerging markets, Asian countries have relative low credit ratings. This leads us to surmise that, in the long term, investors perhaps place more weights on the possibility of sovereign-specific credit events than systemic sovereign credit risks.

As for European countries, for the pre-crisis period, both Italy and Germany have the CDS spreads approximating zero. They also have large pricing errors of 67.30% and 37.81%, shown in Table 9, that can not be ignored. We argue that this leads to the evaluation inaccuracy of the risk premium and the credit-event components in the two countries.

In addition, we also provide the plots of the weights for the risk premiums for one-year, three-year, and five-year contracts for each sovereign in Figure 9. Despite the differences between the plots for different countries, within each country, the distributions for the contracts with different maturities tend to cluster together. Another noticeable feature is that the weights of the risk premiums for all of the countries oscillate around or approximately zero in the post-crisis period. This is consistent with our observation in Figure 8 that the credit-event components weight much more than the risk-premium components for most countries in our study.

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[21]The Philippines has larger spreads than the other Asian countries due to its low credit rating.

Market Price and Risk Premium of 5-year Sovereign CDS for China

Market Price and Risk Premium of 5-year Sovereign CDS for Germany

Market Price and Risk Premium of 5-year Sovereign CDS for Italy

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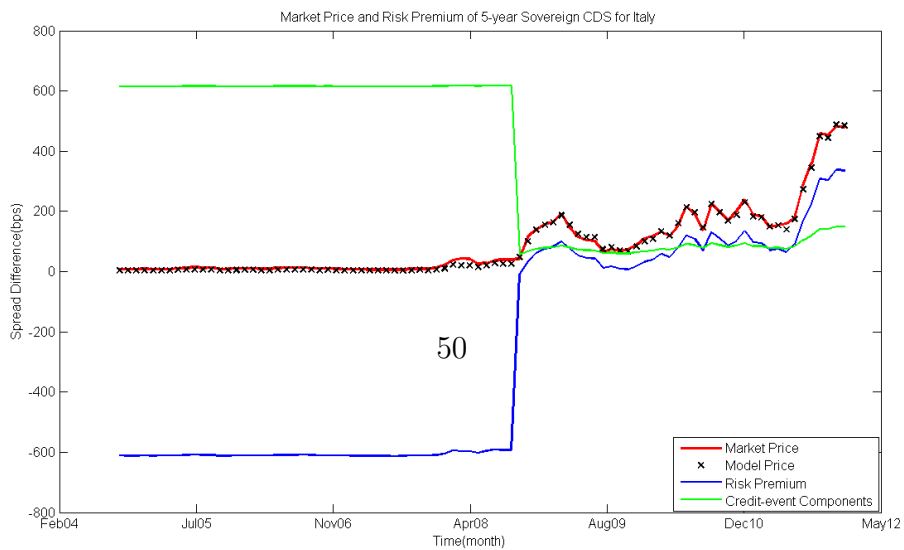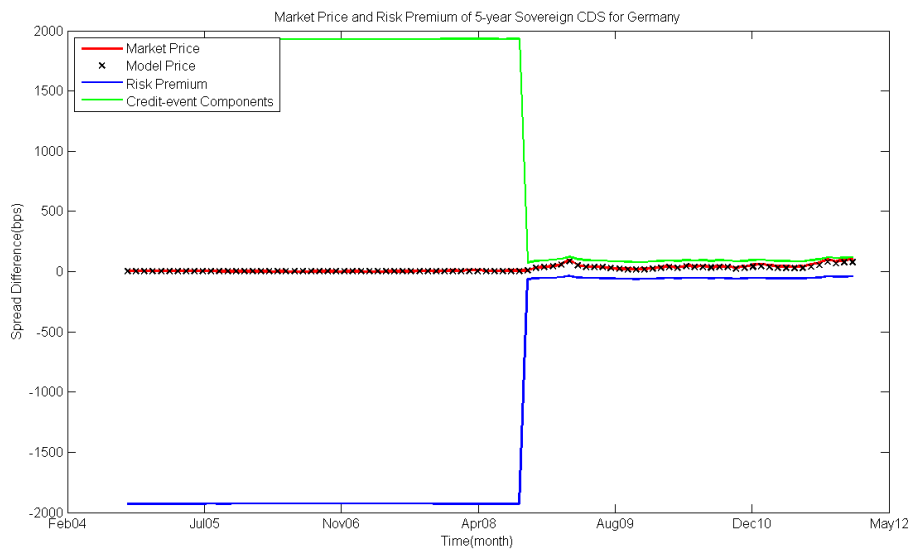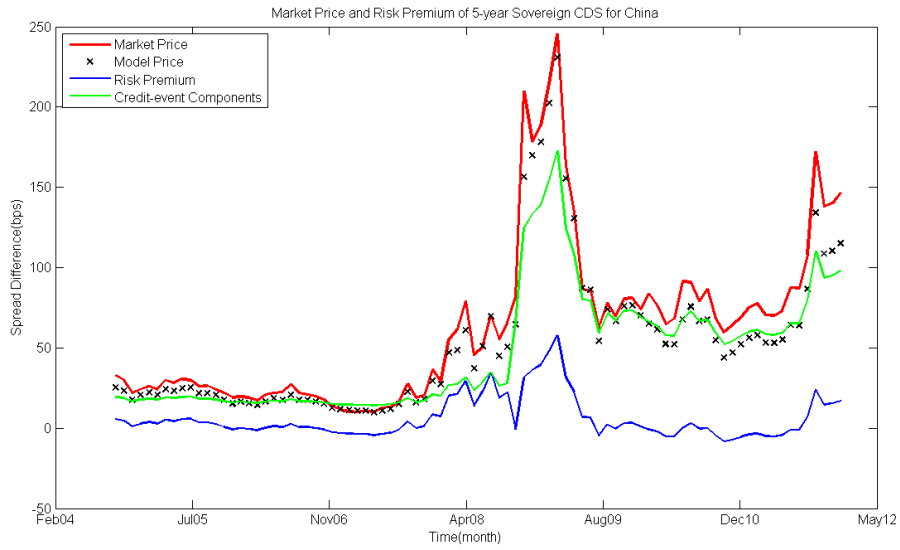
Figure 8: Decomposition of Five-year Sovereign CDS Contracts

Weights of Risk Premium Components for China

Weights of Risk Premium Components for Germany

Weights of Risk Premium Components for Italy

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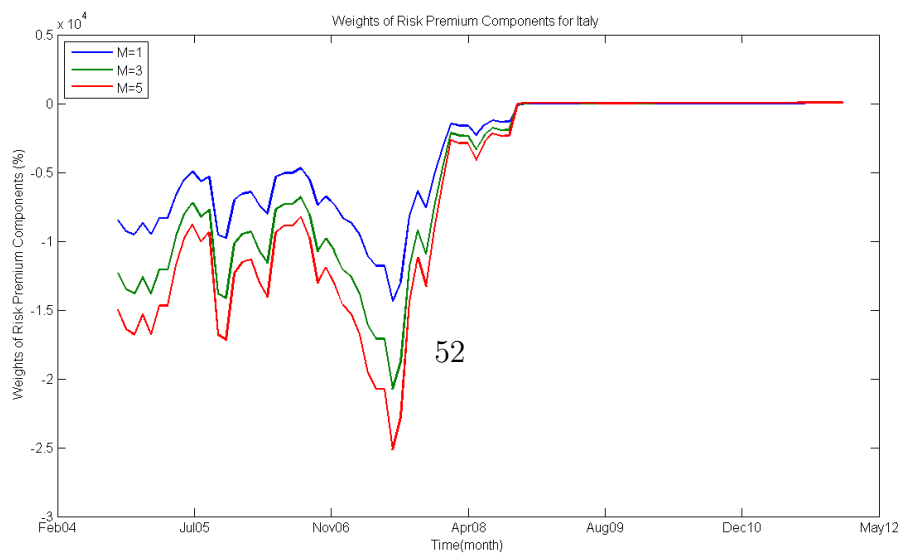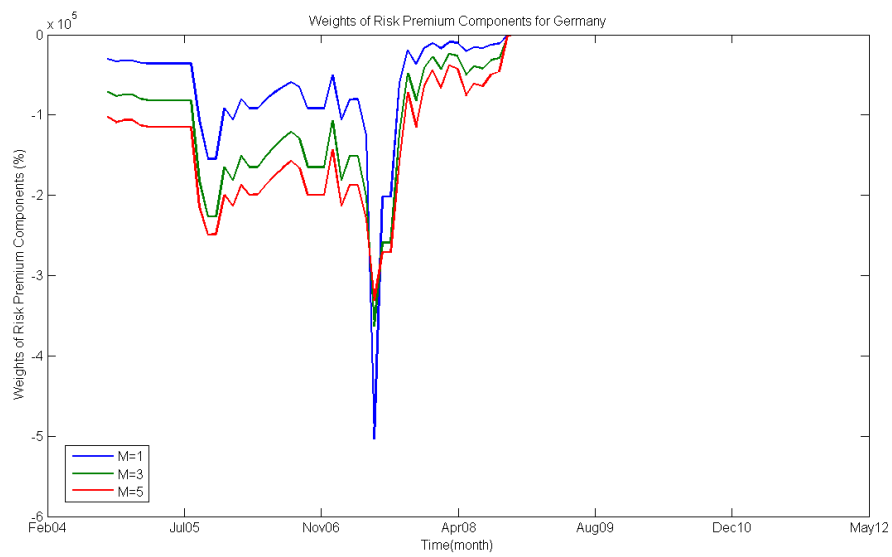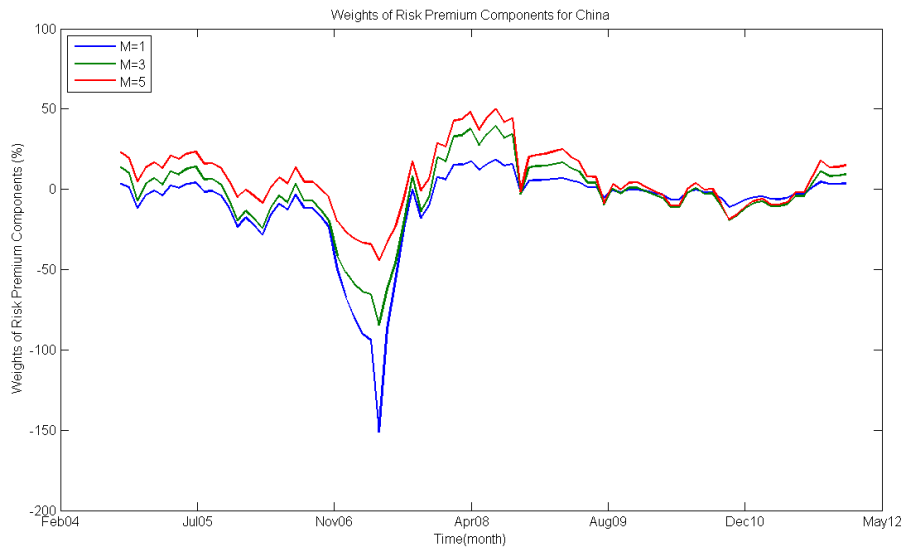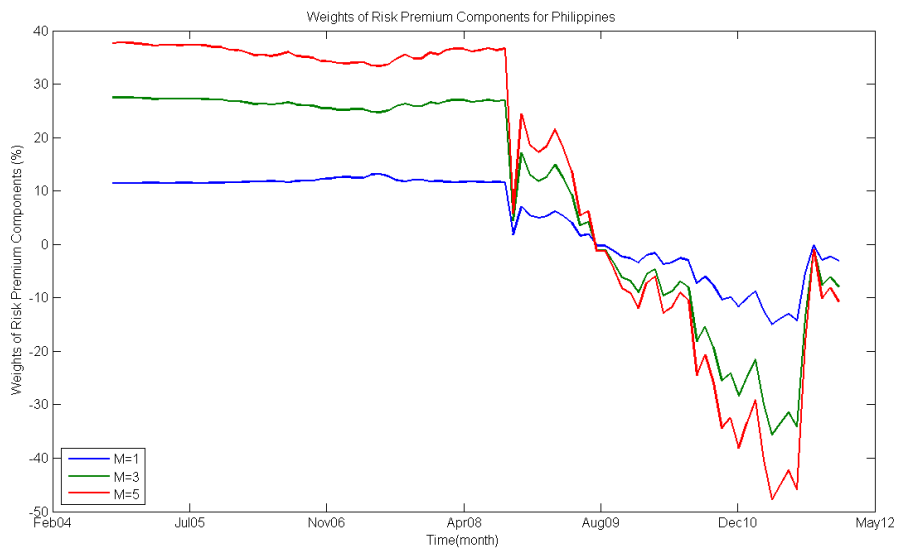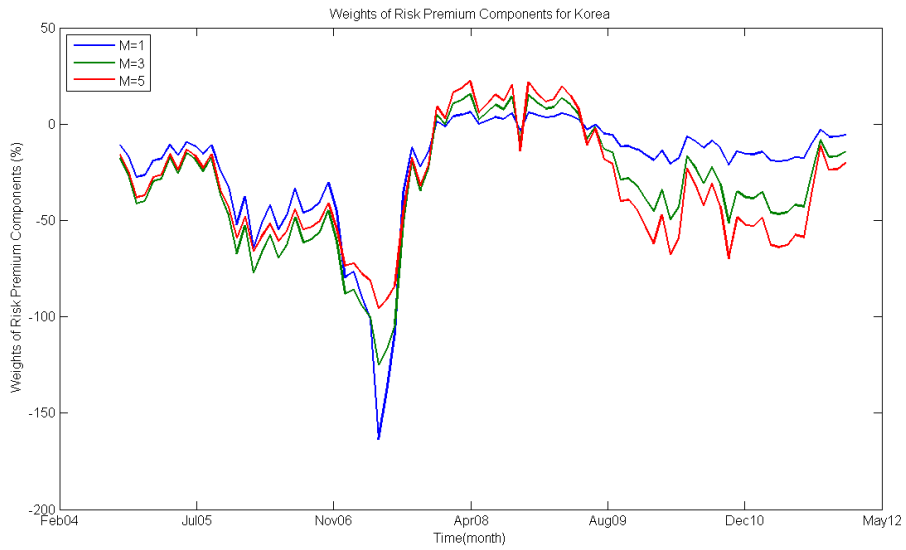
Figure 9: Weights of Risk Premium Components of Five-year Sovereign CDS

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7 Conclusion

In this paper, we have analyzed the nature of the sovereign credit risks via the spread data of sovereign CDS for selected countries in Asia and Europe, which included both developed and developing/emerging countries with various credit ratings. Instead of using sovereign bond data, we followed Longstaff et al. (2011) in using the CDS contracts on the external debt of these countries in an effort to extract information on the likely determinants of sovereign credit risk in these countries. Importantly, these sovereign CDS contracts function as insurance contracts that allow investors to buy protection against the event that a sovereign defaults on or restructures its debt. Thus, sovereign CDS data has the advantage over sovereign bond data in that it allows us to identify directly the investment returns generated exclusively by changes in sovereign credit risk.

Our results showed that the sovereign credit risks have different structures from local stock markets. They tend to have stronger co-movements across countries after the 2008-2009 financial crisis. Regression analyses conducted in this paper indicated that stronger commonality of sovereign credit risks appear to have stemmed from their dependence on a series of economic and financial variables. These variables include local economic variables, global financial market variables, global risk premiums, and other factors embedded in the regional sovereign spreads, such as the liquidity factor. Specifically, we find that some variables, including foreign reserve, global stock market, and volatility risk premium, affect the of Asian and European sovereign credit risks in the opposite direction.

In pricing the sovereign CDS spreads, we used a model studied in Pan and Singleton (2008) and Longstaff et al. (2011). However, different from these authors, we assumed that the arrival rate of credit events follows a Cox-Ingersoll-Ross square-root model. We find that there are important differences in the results between our credit risk pricing model and theirs when we use the maximum likelihood estimation method to estimate the parameters of the modelfor the full sample. Taking into account the possible structural changes in the sovereign credit risks before and after the financial crisis, we divided the full sample into two sub-periods, and estimate the parameters of the model for each sub-period separately. We find that this greatly improved the performance of our model in terms of pricing accuracy.

Following Longstaff et al. (2011), we also decomposed the sovereign credit risk into the distress risk premiums and the credit-event components. The decomposition results showed strong regional features as well. In particular, for Asian countries, the credit-event components play a much more important role in the sovereign CDS markets than the risk premiums. Our analyses also indicated that after the 2008-

2009 financial crisis, the weights of the risk premiums in the total sovereign credit risk tend to dissipate over time.

Notwithstanding the fact that the sub-sample ML estimation provided more reasonable results, our one-factor model still has important limitations in pricing the sovereign credit spreads. Especially, when the financial crisis occurred, the parameters that governed the intensity of credit risks was expected to experience substantial structural changes. To capture this, we can introduce a jump component to the square-root diffusion process for λ, or introduce additional relevant factors into the pricing model. The paper is also constrained by the availability of the sovereign CDS data. A larger data set with various maturities for more sovereigns over a longer period would enhance our understanding of the nature of the sovereign credit risks.

Finally and in broader terms, the evidence assembled in this paper seem to point, to some extent, to the "new" view that commonality in sovereign credit spreads may have stemmed from the sensitivity of these spreads to the funding needs of major investors in the sovereign credit markets. These results, we argue, are important to, and relevant for, policy makers worldwide, and, as a result, more research on this topic is encouraged. This is especially critical given that this perspective on sovereign credit risk has long been overshadowed by the historical focus placed in the past literature on the incentives faced by sovereign debtors to repay their debt. While this is an important issue in itself, it may well have distracted policy makers from addressing the real issues for quite some time.

Appendix A: Local Stock Index

China: Shanghai Stock Exchange Composite Index (Bloomberg symbol: SHCMP:IND), a capitalization-weighted index that tracks the daily price performance of all A-shares and B-shares listed on the Shanghai Stock Exchange.
France: Societe Des Bourses Francaises 120 Index (SBF 120:IND), a capitalization-weighted index of the 120 most highly capitalized and most liquid French stocks traded on the Paris Bourse.
Germany: Deutsche Borse AG HDAX Index, a total rate of return index of the 110 most highly capitalized stocks traded on the Frankfurt Stock Exchange.
Italy: FTSE Italia All-Share Index (ITLMS:IND), a free float capitalization weighted index that comprises all of the constituents in the FTSE MIB, FTSE Italia Mid Cap and FTSE Italia Small Cap indices.
Japan: Tokyo Stock Exchange Tokyo Price Index (TPX:IND), a capitalization weighted index of all companies listed on the First Section of Tokyo Stock Exchange.
Korea: Korea Stock Exchange KOSPI Index (KOSPI: IND), a capitalization-weighted

index of all common shares on the Korean Stock Exchanges.

Philippines: Philippines Stock Exchange PSEi Index (PCOMP:IND), a capitalization-weighted index composed of stocks representative of the Industrial, Properties, Services, Holding Firms, Financial and Mining & Oil Sectors of the PSE.

Spain: Madrid Stock Exchange General Index (MADX:IND), a capitalization-weight index that measure the performance of a selected number of Continuous Market stocks.

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