# Sovereign Credit Risk Analysis for Selected Asian and European Countries

by

Min Zhang

A thesis
presented to the University of Waterloo
in fulfilment of the
thesis requirement for the degree of
Master of Quantitative Finance

Waterloo, Ontario, Canada, 2013

## AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Min Zhang

# Abstract

We analyze the nature of sovereign credit risk for selected Asian and European countries through a set of sovereign CDS data for an eighty-year period that includes the episode of the 2008-2009 financial crisis. Our principal component analysis results suggest that there is strong commonality in sovereign credit risk across countries after the crisis. The regression tests show that the commonality is linked to both local and global financial and economic variables. Besides, we also notice intriguing differences in the sovereign credit risk behavior of Asian and European countries. 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. Further, we assume that the arrival rates of credit events follow a square-root diffusion from which we build our pricing model. The resulting model is used to decompose credit spreads into risk premium and credit-event components.

# ACKNOWLEDGMENTS

Completing my master degree in University of Waterloo is probably one of the most challenging activities of my first 25 years. I put lots of efforts on it, and now they have paid off.

I owe my deepest gratitude to my supervisor, Dr. Adam Kolkiewicz, for his guidance and support of my master's study and research. I would like to warmly thank Dr. Tony Wirjanto and Dr. Ken Seng Tan for their precious suggestions. Special thanks goes to my program coordinator, Mary Flatt, for her constant help in the past two years. Besides, I am grateful to all of my classmates for the time that we worked and had fun together.

And lastly, I am deeply indebted to my parents, Xuehua Zhang and Zhuanfeng Wei, for their endless love and encouragement in the past 25 years.

# Contents

# List of Tables

# List of Figures

# Chapter 1

# Introduction

Nowadays sovereign credit risk draws much attention with the increasing sovereign credit default swap market in terms of both size and volume. 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. (2007) suggested, a better understanding of the nature of sovereign credit risk will help large financial institutions and other market participants to better diversify their global debt portfolios, and affect the capital flows in global financial markets.

Meanwhile, the European sovereign-debt crisis arising in the aftermath of the 2009 global economic crisis has caused deep public concerns. In general, resulting from a combination of both political and economic reasons, this Euro Crisis is seen to have given rise to a systematic sovereign credit risk. Under such circumstances, understanding and analyzing the structure of sovereign credit spreads in Europe is of great importance.

In this thesis, we study the nature of sovereign credit risk by posing a number of research questions: What factors determine and affect sovereign CDS spreads, and to what extent? Does sovereign credit risk in different regions share the common features? How can we price sovereign credit risk?

This thesis is organized in the following structure: In the next chapter, we introduce the data set used in this thesis and explain why we select this particular data. Then in the following chapter, we conduct a principal component analysis on the sovereign CDS spreads of selected countries to find their commonality. Once we establish the strong co-movements of sovereign credit spreads across countries, we use a regression analysis to determine the sources of commonality. The remaining chapters of the thesis focus on the pricing model, the estimates of underlying parameters, and the decomposition of sovereign credit risk, respectively.

# Chapter 2

# The Data

## 2.1 Sovereign Set

As stated in the introduction, this thesis mainly focuses on the sovereign CDS data for Europe and Asia. There are several reasons for this choice:

First, the European sovereign-debt crisis arising in the aftermath of the 2009 global economic crisis has raised public concerns. Europe is important to world economy, not only because it contributes to nearly one fifth of 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, when Greece firstly requested loans to repay its government debts in early 2010, the U.S. stock market suffered a great loss of nearly US$2.5 trillion, which reciprocally impacted the European debt market with more than twice the loss. As a result, there were fears about the increasing sovereign credit risk in the global financial system, according to Ang and Longstaff (2011). This concern and fear was further highlighted by the downgrading of many European countries, the US Treasury, leading financial institutions[1],

[1]Standard & Poor's downgraded the credit ratings of the following countries and banks respectively: downgraded Greece to junk status on April 2010; downgraded U.S. Treasury from AAA to AA+ on August 2011; downgraded nine euro-zone countries including Italy, Spain, Portugal, Cyprus by two notches and

and by the widening credit spreads in all of these countries.

Given this background, the thesis considers four large countries in the European Union, which are France, Germany, Italy and Spain, in order to capture the features of these sovereign CDS spreads.

**Table 2.1:** Standard & Poor Credit Rating for Sovereigns*

<table>
<tr><th>Entity</th><th>Local Currency Rating</th><th>Foreign Currency Rating</th><th>Standard & Poor Rating Criteria</th></tr>
<tr><td>China</td><td>AA-</td><td>AA-</td><td rowspan="8">AAA: Best credit quality, extremely reliable<br>AA: Very good credit quality, very reliable<br>A: More susceptible to economic conditions,<br>still good credit quality<br>BBB: Lowest rating in investment grade<br>BB: Caution is necessary,<br>best sub-investment credit quality</td></tr>
<tr><td>France</td><td>AA+</td><td>AA+</td></tr>
<tr><td>Germany</td><td>AAA</td><td>AA</td></tr>
<tr><td>Italy</td><td>BBB+</td><td>BBB+</td></tr>
<tr><td>Japan</td><td>AA-</td><td>AA-</td></tr>
<tr><td>Korea</td><td>AA-</td><td>A+</td></tr>
<tr><td>Philippines</td><td>BB+</td><td>BB+</td></tr>
<tr><td>Spain</td><td>BBB-</td><td>BBB-</td></tr>
</table>

* Datasource: Standard & Poor Website, retrieved on Nov. 2012

Table 2.1 shows the current Standard & Poor credit rating for all of the sovereigns selected in this paper. As shown in the table, Germany maintains a triple A rating, which indicates extreme reliability and best credit quality. Actually, Germany is selected because it is currently the healthiest and strongest economy in Europe. It is also a good representative of the northern European countries, which "managed their finances well and lubricated the rustier parts of their economie" (Unit and Britain, 2011). Similarly, the reason to select France is due to its reasonably good economic condition. Although France was downgraded to AA+ in the January of 2012 by Standard & Poor, it has still a relatively safe credit rating. Conversely, Italy and Spain are listed as the typical sovereigns struggling through debt crisis with huge deficits and face difficulties to pay off their government debts[2]. Spain now has a BBB- credit rating, which is only one rating

France, Austria, Malta, Slovakia and Slovenia by one notch on January 2012; downgraded three French banks including BNP Paribas on October 2012 etc.

[2]Actually we also planned to include Greece in my list of sovereigns. But later we found that the Greece sovereign CDS spread was too large in the past two years (greater than 100% sometimes). Therefore we

away from the devastated level. Italy is a bit better than Spain with a BBB+ rating. Besides, all of the four countries are 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 world and fourth largest in Europe; and Spain is the sixth largest in Europe. From a practical point of view, large economies are more attractive of study since they have larger influences over the world economy compared to small economies such as Malta and Cyprus.

Second, ever since early 1990s, China's economy has started to take off, fueled by its efforts to transform from a planned to market oriented economy, which gradually became a new booster of global economy, as Chow (1994) stated. Actually, as the second largest economy in the world ((IMF), 2012), given China's fast economy growth rates, large GDP and purchasing power parity, great exporter and importer capacity, and large foreign exchange reserves,China has increasingly exerted its vital role in the world. However, despite its ongoing reforms, China's economy is seen to exhibit quite distinctive features relative to those in rest of the world, in terms of its macro-control economic system and limited economic access. In particular, according to Zhu and Lague (2012), the state-owned enterprises dominate the country's economy: these"state companies and affiliated businesses account for more than half of China's economic output and employment"; they seem to exert control over key industries and resources in China such as energy, electric, steel, telecoms, transportation, and finance.

Taking the distinctive features into consideration, it is interesting to investigate China's sovereign CDS spreads. The following research questions naturally: What factors determine and affect China's sovereign CDS spreads, and to what extent? Do they share the same dependencies as those of the other major countries? Can they be priced using the same methodology? If not, what are the modifications needed for China?

exclude from our study the chaotic sovereign CDS spreads of Greece.

Besides China, three other countries, Japan, South Korea and Philippines in Asia are selected to be studied in this thesis. In this way, it is possible to analyze the degree and nature of sovereign CDS spreads co-movements in both Europe and Asia, thereby the potential regional factors that may influence these spreads. Japan is the third largest economy in the world, only after US and China, with the same AA- credit rating as China. South Korea is one of the actively traded sovereign credits, and one of the G-20 major economies. Philippines stands for these small economies in Southeast Asia with relative low credit ratings.

## 2.2 Sovereign CDS Market

Credit default swaps (CDS) are bilateral contracts in which two counterparties exchange periodic premiums, typically expressed in basis points on the notional amount as CDS spread, with a contingent payment 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; albeit 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; Bluhm et al., 2002).

To identify a CDS contract, the following pieces of information are required: reference obliger and his 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 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 CDS spread per notional amount, and protects the contract buyer with contingent payment once the credit event occurs. However, the definition of credit events for a sovereign CDS is usually different. Typically, the credit events include: obligation acceleration, failure to pay, restructuring and repudiation/moratorium (Pan and Singleton, 2008)[3]. Besides, when physical delivery is needed for settlement, only bonds denominated in standard specified currencies[4] in external markets are deliverable. For sovereign issuers without such bonds, loans will be included in the set of deliverable assets.

As Pan and Singleton (2008) mentioned, currently in the global sovereign CDS markets, contracts with five-year maturity have the best liquidity, accounting for about 40% of the market volume. Three-year and ten-year contracts are also popular, which cover about 1/5 of the volume separately. So this thesis places emphasis on five-year sovereign CDS contracts of the eight selected countries from Asia and Europe for the past eight years, 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 financial crisis. Data are obtained from the Bloomberg data base, which gathers CDS quotation from other industry sources. All of these CDS contracts are US dollar-denominated.

## 2.3 Summary Information

In summary, this thesis is based on the five-year sovereign CDS spreads data of China, France, Germany, Italy, Japan, Korea, Philippines, and Spain from September 2004 to August 2012. This data set not only covers a wide range of credit qualities, but also achieves a balanced regional representation in Europe and Asia. This thesis also considers a liquidity factor. Since according to Pan and Singleton (2008), "the levels of CDS spreads

[3] Note that default is not included in the credit event definition, since "there is no operable international bankruptcy court that applies to sovereign issuers".

[4] Standard specified currencies consist of any of the lawful currencies of Canada, Japan, Switzerland, the United Kingdom, the United States and the Euro, according to the ISDA.

are largely reflective of credit asseements, as opposed to illiquidity".

Figure 2.1 plots the daily sovereign CDS spreads for the selected Asian and European countries separately. As shown, the credit spread structures of countries in the same region exhibit interesting dynamics. For each region, there are strong co-movements among all of the sovereign CDS spreads. Another noticeable feature is the distinct pattern of spread movements between Asia and Europe. For the Asian region, the maximum and most volatile spreads occurred from 2008 to 2009, and they recovered quickly 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 has started to increase gradually. Then the European CDS spreads peaked in 2011 and 2012. And the highest peak occurred in the past two years, which is much larger than the spreads around 2008. Thus, although both influenced by the financial crisis and the Euro Debt crisis, Asian countries are affected to a larger degree from the former crisis, while European countries have been affected more substantively only after the crisis. This thesis also finds that in Asia, the spreads of Philippines, Korea, China, and Japan are consistently ranked highest to lowest respectively, and the spreads of China and Japan are quite close. In Europe, Spain has the largest spreads, and Italy follows next.

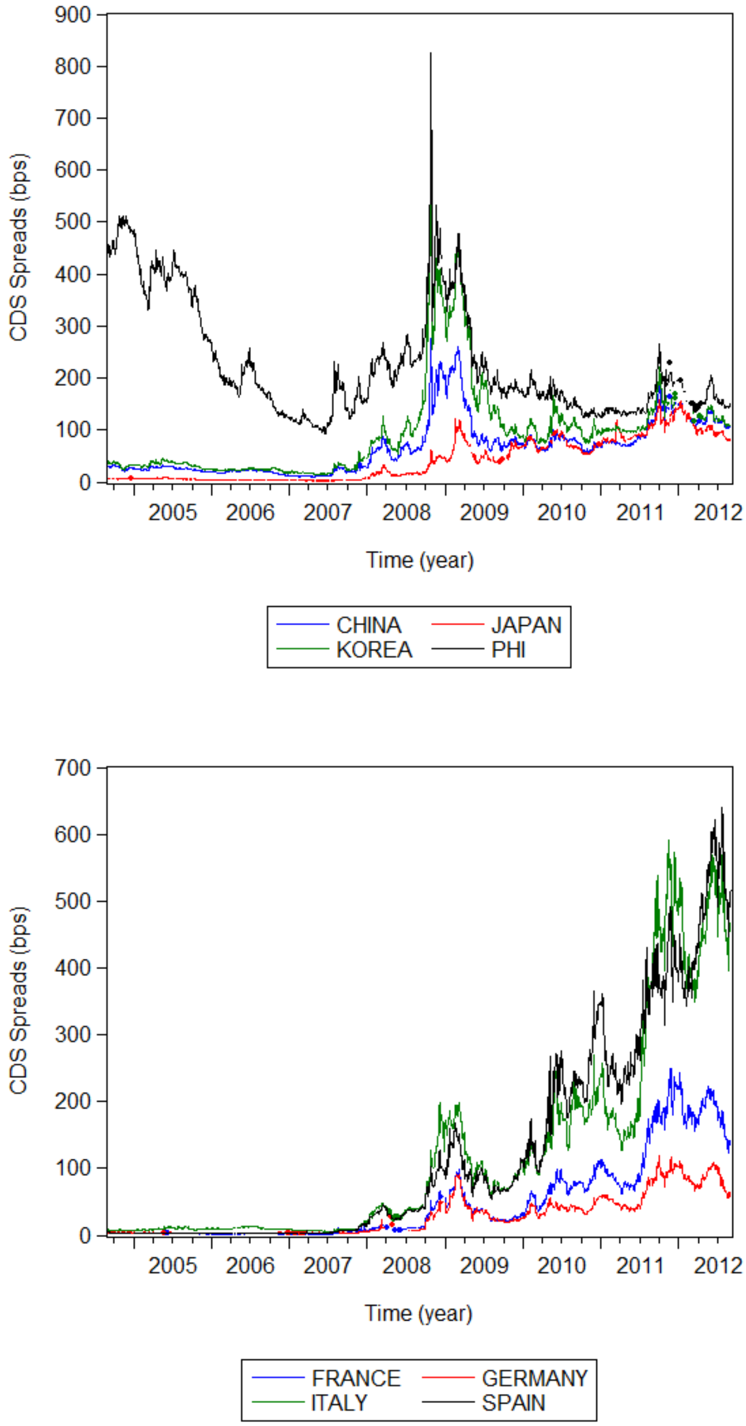



**Figure 2.1:** Plots of Daily Sovereign CDS Spreads from Sept 2004 to Aug 2012

**Table 2.2:** 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 autocorrelation statistic.

Table 2.2 provides descriptive statistics for the daily sovereign credit spreads. As shown in the table, the range and mean of CDS spreads vary considerably from country to country: Germany has the smallest mean, 29.978 basis points (bps), and the smallest range, 117.033 bps; France, Japan and China come next only to Germany with means around 50 bps and ranges less than 300 bps; Korea has an average spread less than 100 bps; Italy and Spain have quite close means around 120 bps and similar ranges around 600 bps; Philippines has the largest range, minimum, maximum, mean and median spreads among all the countries. This is consistent with our earlier observation on the spread plots.

Table 2.2 also reports the sample first-order autocorrelation coefficients for the sovereign CDS spreads of each country. As shown, all of them are strongly auto-correlated. For a further analysis of this property, the sample autocorrelation and partial autocorrelation coefficients for the first fifty lags are calculated and plotted in Figure 2.2 and Figure 2.3 with approximate 95% confidence intervals. The significant sample autocorrelations of CDS spreads, which tail off gradually with increasing lags, are visible in Figure 2.2; while

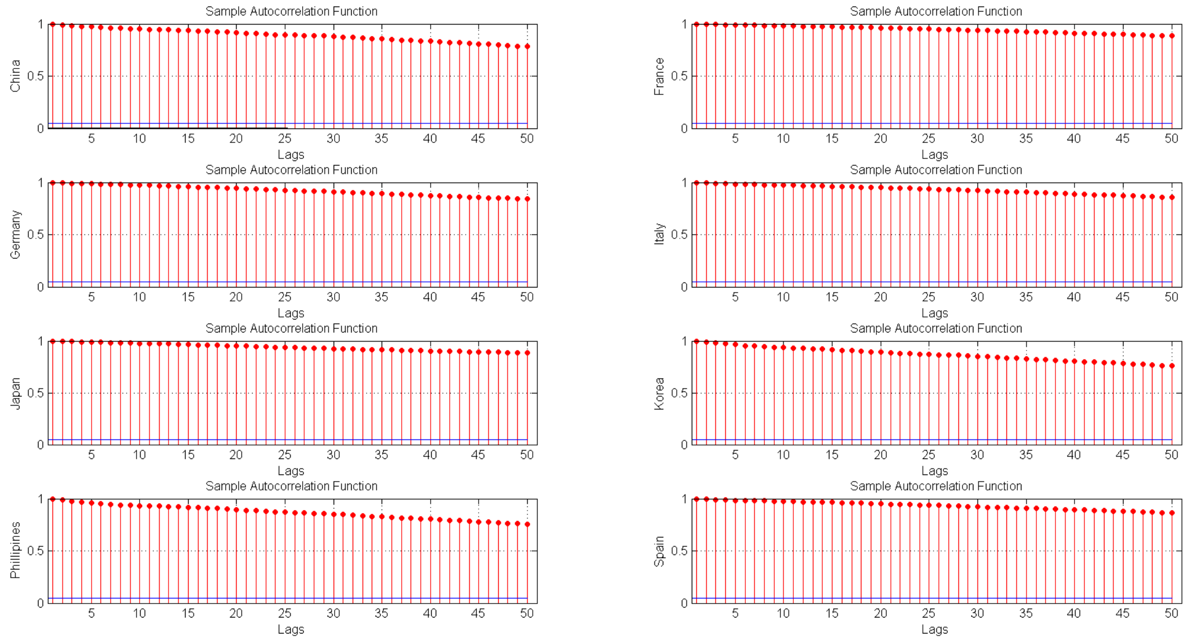



**Figure 2.2:** Sample Autocorrelations of Daily Sovereign CDS Spreads from Lag 1 to Lag 50

in Figure 2.3, the sample partial autocorrelations 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. In general, these analyses indicate that sovereign CDS spreads are strongly autocorrelated over time. Besides, we conduct a goodness of fit test on the first difference of CDS spreads for each country. Figure 2.4 shows the Q-Q plots of these first differences against the referenced normal distribution for selected countries. It seems that none of them is close to a normal distribution.

Comparing Table 2.1 with Table 2.2, we can draw the conclusion that the range, mean, and standard deviation values of the CDS spreads for each country correlate with the credit quality of this 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 sovereign CDS spreads. As Bluhm et al. (2002) stated, credit rating of a country represents its creditworthiness, and a low credit rating indicates a high default

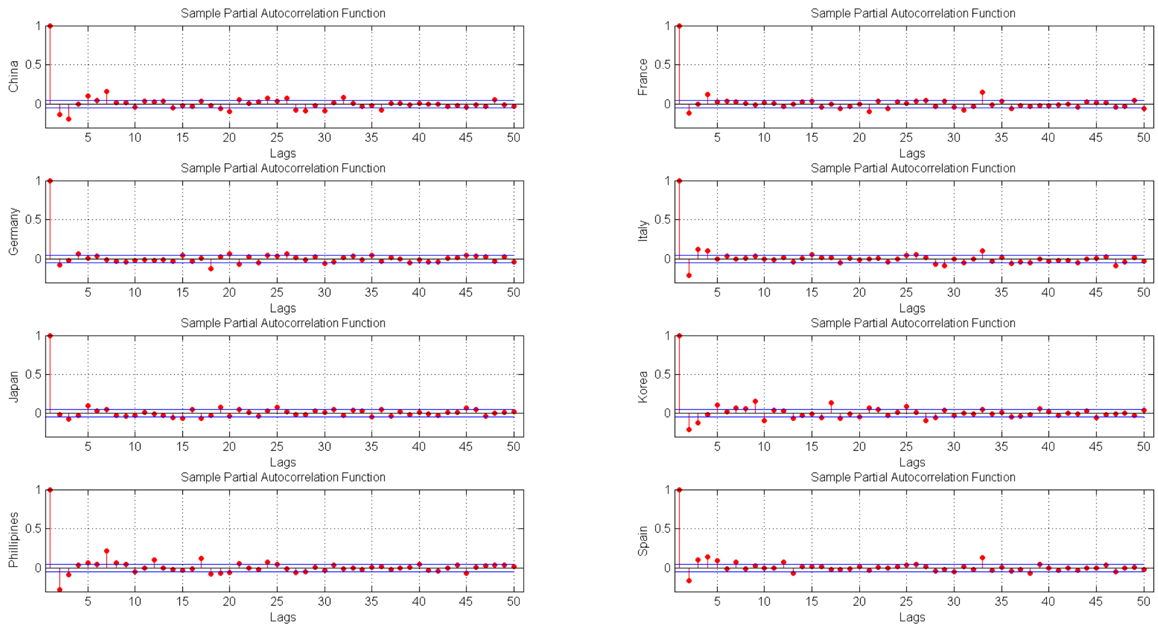



**Figure 2.3:** Partial Autocorrelations of Daily Sovereign CDS Spreads from Lag 1 to Lag 50

probability on its debts. It is sovereign CDS contracts that protect investors from this default risk on sovereign bonds. Of course the contract prices, namely the CDS spreads, are higher for countries with higher default probabilities. Especially when these countries suffer from great changes in credit qualities, their sovereign CDS spreads will become more volatile and contribute to a large variance.

The above observation applies to these sovereign CDS spreads before and after the crisis. As we can see in Table 2.2, the average spread of Philippines is almost twice as much as the second largest average spread. Recall that except for 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 2.1. Nevertheless, after the crisis, due to the increased global credit risks and the generally downgraded credit ratings, all of these countries are strengthened to different extents, especially for Italy and Spain.

Korea is the only exception to the case in terms of the contrast between its relatively

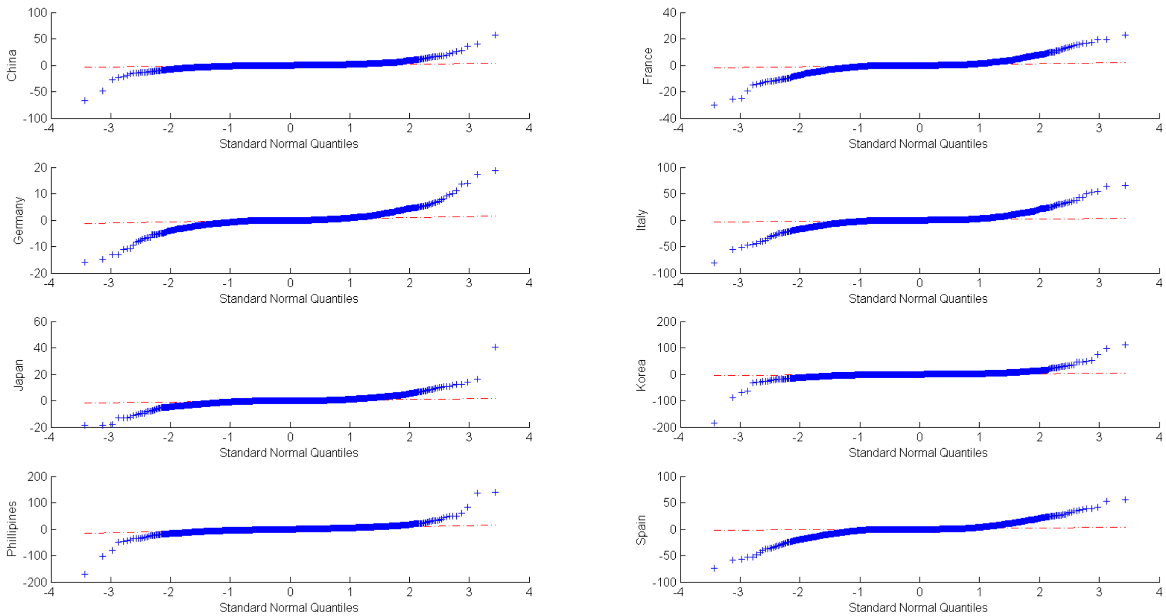



**Figure 2.4:** Q-Q Plots of Daily Sovereign CDS Spreads against Normal Distribution

good A+ credit quality and its large range and maximum values of sovereign CDS spreads. Further research shows that Korea's credit rating was upgraded three times this year due to the reduced geopolitical risks benefiting from the smooth change 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 credit spreads. It is also noticeable that all of these countries have quite outstanding values of standard deviation compared with the values of the mean. Half of them have larger values of standard deviation than the average values of spreads. This implies the substantial time series variations during the sample period.

Cross correlation tests on the daily changes of sovereign CDS spreads indicate that they are pairwise correlated. The sample correlation matrices are calculated and reported in Table 2.3. As shown in Table 2.2, all of these eight countries have different sizes of sample data, so their sample correlation are calculated based on days for which the spreads

**Table 2.3:** Correlation Matrix for Daily Changes of Sovereign CDS Spread

| Time Period | | China | France | Germany | Italy | Japan | Korea | Philippines | Spain |
|---|---|---|---|---|---|---|---|---|---|
| Sept 2004 - Aug 2012 | 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 |
| | 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 |
| Sept 2004 - Aug 2008 | 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 |
| | 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 |
| Sept 2008 - Aug 2012 | 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 |
| | 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 |

overlap. Moreover, to further check the nature of sovereign CDS spreads and analyze the potential changes in their co-movements before and after the financial crisis, we divide the eight-year sample period into two sub-periods, which are the pre-crisis period from Sept 2004 to Aug 2008, and the post-crisis period from Sept 2008 to Aug 2012.

The first part of Table 2.3 present their sample correlation over the full sample period. These positive correlation indicate that all of the sovereign CDS spreads are positively correlated with each other, providing the evidence of their co-movements. Besides, we notice that the pairwise correlations between any two counties in the same region is always stronger than those in different regions. For example, the correlations between China and other Asian countries are larger than the correlations between China and European countries; while France is much more strongly correlated with Germany, Italy, and Spain than with Asian countries (Average: 70% vs 22%). Based on this evidence, it is reasonable to assume that the regional factor is one determinant for sovereign credit risk.

The second and third parts of Table 2.3 show the sample correlation matrices in the pre-crisis and post-crisis periods respectively. The pairwise correlations have increased dramatically after the 2008-2009 crisis. The average magnitude of correlation is about 10% from Sept 2004 to Aug 2008, and 41% from Sept 2008 to Aug 2012.

The most noticeable changes take place in the correlations between Germany and Asian countries: before the crisis, the changes of sovereign CDS spreads of Germany were negatively correlated with those of China, Japan, Korea and Spain; but these correlations turned to be positive after the crisis.

Similarly, recent research of Dahlquist and Hasseltoft (2011) observes increased correlations between international bond risk premia. We argue that these phenomena indicate the increased systematic sovereign credit risk in global financial markets, as well as the increased integration between financial markets following the crisis. This also confirms the assertion by Ang and Bekaert (2002) about the tendency for correlations between international financial markets to increase in highly volatile bear markets.

# Chapter 3

# PC Analysis of Sovereign CDS Spreads

Now that the correlation matrices suggest close relations between sovereign CDS spreads, in this section we focus on the commonality analysis on these spreads. To implement this analysis, we use the principal components (PC) analysis method to investigate the daily changes in sovereign credit spreads. For reference, we also conduct the same analysis on the stock index returns for the selected countries, and interpret the PC analysis result by calculating its sample correlation coefficient with several US stock indices as well.

As stated in Jolliffe (2005), PC analysis is widely used to "reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set". Note this is less true for data that are highly nonlinear and non Gaussian as is the case with most financial variables. Via PC analysis, the data set is transformed into the principal components (PCs), which forms a new set of ordered uncorrelated variables.

By conducting the PC analysis on the covariance matrices of daily sovereign credit spread changes, we are able to identity the commonality in these CDS premiums. Similar to Table 2.3, the covariance matrices are based on the overlapping daily spreads data, and calculated for the total sample period, pre-crisis and post-crisis sub-periods, respectively. In this way, we can compare and recognize the latent changes in global sovereign CDS markets, since our previous analysis implies there may be increased correlations after the crisis.

## 3.1 Reference Point

Additionally, to provide more insights, we also use the data set of domestic equity indices for the eight countries as a reference point. This reference set describes the returns of local stock market. The detailed list and description for these equity indices from Bloomberg data base can be found in Appendix A.

Before the PC analysis, we also calculate the pairwise correlations of these index returns for the total sample period and two sub-periods, shown in Table 3.1. Similar to the correlation matrix of CDS spread changes, there are strong correlations between the index returns, and the pairwise correlations between the indices in the same region is always larger than for cross-region indices. However, we still notice the differences between the two correlation matrices: For both sub-periods, the pairwise correlations between the index returns are always positive, which is quite different from the matrix for CDS spreads in pre-crisis period; the average values for indices in the two sub-periods are quite close (40% vs 45%), while there is a huge increase in average values for spread changes (10% vs 41%). This suggests the correlation structure differences between the sovereign CDS spreads and local equity returns. Other than local equity returns, variables such as other global economic and regional factors may influence the changes of sovereign credit spreads.

## 3.2 PC Analysis Results

Based on the these correlation matrices, we conduct the PC analysis on daily changes of both sovereign CDS spreads and local stock markets daily returns Table 3.2 provides the results for the entire sample period as well as the two sub-periods. For the sovereign

**Table 3.1:** Correlation Matrix for Local Index Returns

| Time Period | | China | France | Germany | Italy | Japan | Korea | Philippines | Spain |
|---|---|---|---|---|---|---|---|---|---|
| Sept 2004 - Aug 2012 | 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 |
| | 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 |
| Sept 2004 - Aug 2008 | 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 |
| | 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 |
| Sept 2008 - Aug 2012 | 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 |
| | 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 |

CDS spreads, the results imply strong patterns of commonality during the whole sample period: The first PC explains 46.96% of the variation of 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 captured and explained by the first three PCs.

Meanwhile, the large differences for the first and second PCs before and after the financial crisis should be noticed. In the pre-crisis sub-period, the first PC itself only explains 25.07% of the variation, while the second PC explains about 18% of the variation; however after the crisis, the explanation power of the first PC increases to 48.95%, while the second PC counts for more than 25% of the spread variation. Considering the reinforcement of the total percentage explained by the first two PCs, it seems that part of the influences, or explanation power, of the other PCs are transferred to the first two PCs after the financial crisis. The increased commonality among spreads after the crisis is consistent with the statement of Ang and Bekaert (2002) about tendency of increased correlations among international financial markets, as we have mentioned earlier.

Turning to the local stock returns, over the entire period, 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 commonality in the behavior of the local stock markets for the eight countries. Besides, in contrast to the analysis results of CDS spreads, there are basically no changes on the percentage explained by each PC of stock returns, with the total percentage explained by the first three PCs remains stable at around 85%. This is another evidence for the structural differences between sovereign credit spreads and local stock market returns.

Figure 3.1 plots the loadings for the first three PCs for the entire sample period, the pre-crisis sub-period, and the post-crisis sub-period in turn. Consistent with the results in Table 3.2, loadings for the entire sample period are quite close to those of the post-crisis period.

Focusing now on the full sample period, loadings for first PC follow roughly a uniform

**Table 3.2:** PC Analysis Results

| Time Period | Sovereign CDS Spreads | | | Local Stock Returns | | |
|---|---|---|---|---|---|---|
| | PCs | % Explained | Total | PCs | % Explained | Total |
| Sept 2004-Aug 2012 | 1st | 46.96 | 46.96 | 1st | 53.06 | 53.06 |
| | 2nd | 25.00 | 71.96 | 2nd | 20.75 | 73.81 |
| | 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 |
| Sept 2004-Aug 2008 | 1st | 25.07 | 25.07 | 1st | 52.14 | 52.14 |
| | 2nd | 18.12 | 43.19 | 2nd | 20.95 | 73.09 |
| | 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 |
| Sept 2008-Aug 2012 | 1st | 48.95 | 48.95 | 1st | 54.46 | 54.46 |
| | 2nd | 25.48 | 74.43 | 2nd | 20.90 | 75.36 |
| | 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 |

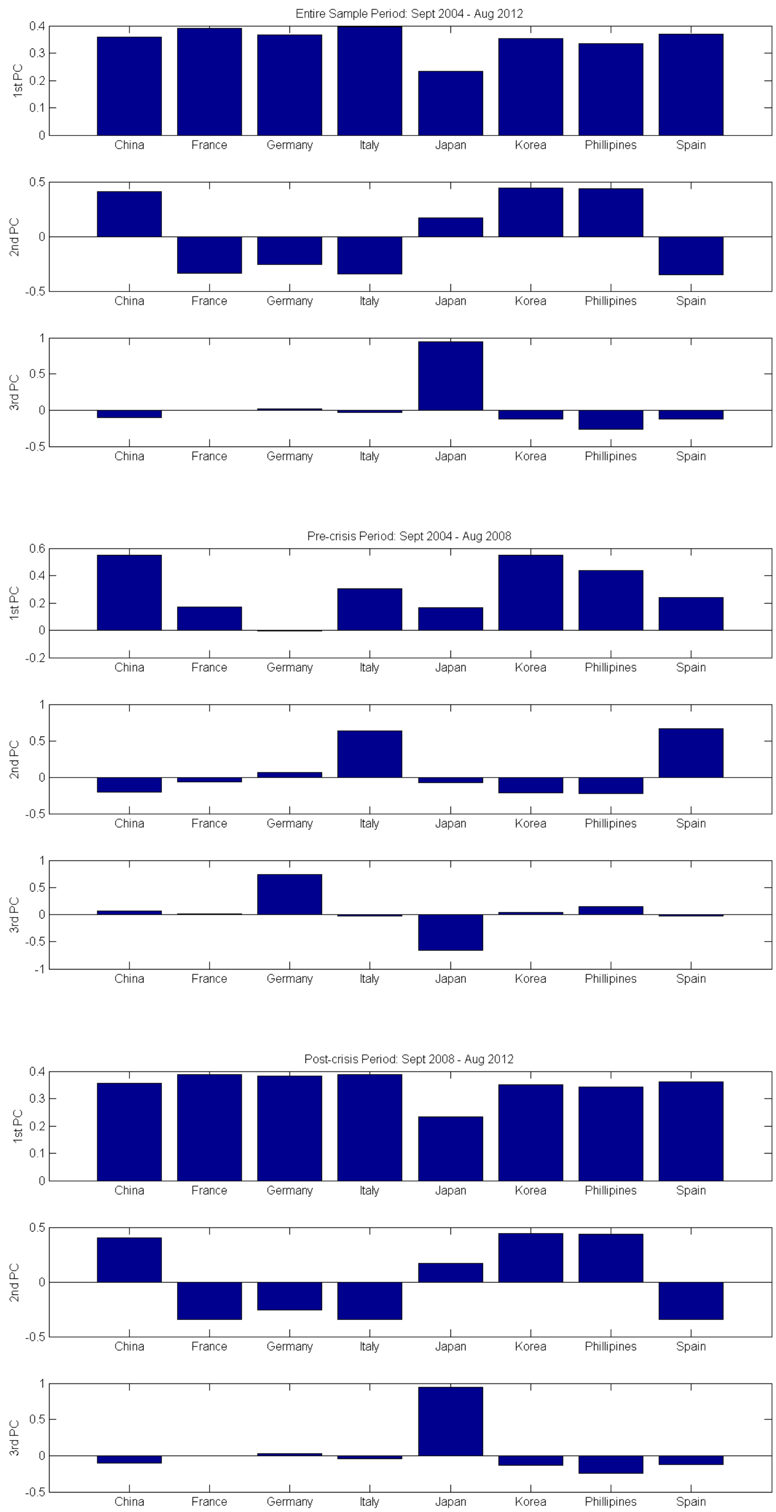



**Figure 3.1:** Loadings for First Three PCs of Daily Sovereign CDS Spreads Changes

distribution. This indicates the first PC represents certain global factors, and these global factors have similar influences on sovereign credit spreads for different countries. As for the second PC, all of the loadings for Asian countries are positive while those for European countries are negative. One possible explanation for this result is that the second PC represents some regional factors.

To further interpret the first two PCs, we exploit their time series to analyze their correlations 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 safer to draw the conclusion that the first principal variation source of sovereign CDS spreads is at least partially correlated with the US stock markets measured by various stock indices and equity market volatility. This is basically consistent with the findings of Longstaff et al. (2007), who reported strong negative correlation between first PC and US stock markets.

For the time series of the second PC, we calculate the difference between the daily return of the EURO STOXX Index[1] and the daily return of the MSCI Asia APEX 50 Index as a simple proxy for a 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 period, and is -39.29% over the latter part of the sample, which reinforces our assumption about the second PC to a certain extent.

[1]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 widely followed as a benchmark by investors investing in Asia.

# Chapter 4

# Sources of Commonality

According to McGuire and Schrijvers (2003), the spreads co-movements on bond debt across countries suggests that they are driven by one or more common factors. This is consistent with our analyses in the last chapter, which provide the evidence of strong commonality among the changes of sovereign credit spreads. Here by commonality, we So naturally in this chapter, we try to explore the sources of this commonality. Using a similar exploration to the one presented by Longstaff et al. (2007), we introduce a combination set of local economic variables and global macroeconomic factors, and investigate their influences on sovereign credit risk. Because it is difficult to collect the daily data for some macroeconomic factors, here in this chapter we use monthly data to analyze the commonality among sovereign CDS spreads.

## 4.1 Set of Variables

As Longstaff et al. (2007) argued, because there are unlimited numbers of variables that may affect sovereign credit risks, we should be cautious about the selected variables. Although the literature varies widely in the choices of variables and methodologies, relevant economic factors actually has been identified in the literature.

Grossman and Van Huyck (1989) stated that the defaults of sovereign debts are related to the bad states of the economy. McGuire and Schrijvers (2003) argued that a common variation in emerging-market debt spreads is largely explained by investors' attitudes towards risks. The study of Baek et al. (2005) showed that economic fundamentals and market's risk attitudes on sovereign risk premiums. Similarly, Remolona et al. (2007) decomposed sovereign CDS spreads into expected losses from default and market risk premia required by investors as compensation for default risk. Their results indicated the associations between sovereign credit risk and country-specific fundamentals as well as global investors' risk aversion. Baldacci et al. (2008) focused on the determinants of sovereign CDS spreads in emerging markets, and found that both fiscal and political factors matter for 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 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.

It is natural for us to start from local and global economic factors for the choices of the explanatory variables, which can be reflected by a series of market-oriented variables. Risk premiums are also included as significant sources of sovereign CDS spreads. Besides, we notice that some literature listed above mainly focus on emerging markets (e.g. Remolona et al., 2007, Baldacci et al., 2008, Hilscher and Nosbusch, 2010), whilst some other studies placed emphasis on European markets (e.g. Attinasi et al., 2009). In this thesis, our data set is made up of sovereign CDS data of selected Asian and European countries, where Asian countries are treated as the emerging markets. Given 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

Among all the these possible variables that affect the sovereign credit spreads, local economic variables are the most important ones. Similarly to Longstaff et al. (2007), we select the 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* - As it is well known, the stock market monitors and responds to developments in the overall economy. When the stock market rallies, people become wealthier and spend more, and investment spending is stimulated as well(Mankiw, 2011). As mentioned in Section 3.1, we calculate the monthly returns of local stock markets for the eight countries from September 2004 to August 2012 via the corresponding local equity indices. All the indices are denominated in units of local currencies.

*Exchange Rate* - Interacting with other economies in the world by buying and selling goods and services in world product markets and capital assets in world financial markets, an open economy is influenced significantly by its exchange rates, which measure the prices of these international transactions (Mankiw, 2011).Thus exchange rate should be considered as one of the local economic factors.

According to Aristovnik and Čeč (2009), most raw materials are now traded in US dollars, and this currency covers more than four-fifths of foreign trades and one-half of global exports. Therefore, US dollars is widely accepted as the world currency. So we define the exchange rate as the value of one unit of the local currency in terms of the US dollar. The data of exchange rates are obtained from Bloomberg data base, and then we calculate their monthly percentage changes for regression purpose. Note that sometimes there are not much fluctuations in exchange rates, for example the rate of CNY/USD remained steadily at 0.1208 from September 2004 to March 2005, then the percentage change of zero is included in the regression.

*Foreign-exchange Reserves* - Foreign-exchange reserves refer to foreign currency deposits and bonds held by central banks. Thus the changes in 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, to provide proper amounts of international payments, to support a favorable economic environment, and to reduce the risks of speculatively induced collapse (Palley, 2004). In addition to these roles, there is one apparent linkage between the foreign reserve and the 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., 2007). The higher the reserves are, the lower the sovereign risk should 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 obtained from 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 discussed before, all of the countries, or at least countries listed in this paper, are open economies and they interact with other economies in global markets. Thus, as suggested in the literature and in practice, their sovereign credit risks and risk premiums rely not only on their local economic states, but also on their global macroeconomic factors. Moreover, the progressive 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 intensifies the dependences dependence of open economies on global factors. As Mauro et al. (2002) stated, nowadays sharp changes on sovereign bonds tend to be mostly related to global events than country-specific events, and this correlation tend to be stronger than they were historically.

Different from the case for the local economy, sometime it is hard to find proper measures of global macroeconomic factors. In order to capture the general characteristics and broad movements of global economy, we use relevant measures of U.S. economy as proxies as suggested by Longstaff et al. (2007). As the world's largest economy, the United States plays a vital role in the global economic and financial markets. Additionally, U.S. is not included in the eight countries selected in this thesis. For instance, some researchers have reported the high correlations between its 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; Goetzmann et al., 2001).

*Global Stock Market* - Consistent with local variables, we place the global stock market as the first element of 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 US stock market by including all of US headquartered equity securities with readily available price data. Note that unlike the calculation of local stock market returns, here we calculate the excess returns of this index by deducting the U.S. one-month Treasury bill rate from the index return rates. The one-month Treasury bill rate plays the role of risk free interest rate here, following Fama and French (1993). The data is obtained from Bloomberg data base with 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 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).

Under such circumstances, there is no reason to exclude this large and dominant market from the list of our global economic variables. Following the setting in Longstaff et al. (2007), 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 to 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 Bloomberg data base under symbol CMAT05Y.

*Investment-grade & High Yield Bonds* - Sometimes, investors are tempted 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 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. 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 also an issue with this measurement, that is, the five-year Industrial AAA bond index was discontinued on March 2012[1]. Thus, for the four months from April 2012 to August 2012, we 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 a concern about these common external factors, which are essentially the default risk components, comprised of a set of fundamental variables determining creditworthiness. Nevertheless, many researchers have also noticed the phenomenon of the credit spread puzzle, that is, the component of credit spreads driven by default risk factors only accounts for parts of the sovereign credit spreads.

For instance, in the corporate credit spread literature, Berndt et al. (2004) and Driessen (2005) decomposed corporate bond spreads into expected losses from default and the default risk premium. The latter is also referred 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 intensity factors, but also found the dramatic variation in the risk premia over time. Similarly, in the sovereign credit spread literature, Baek et al. (2005), Remolona et al. (2007), 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

[1]According to Bloomberg analysts, the possible reason for this discontinued index is the widespread downgrading of these original AAA corporate bonds after the crisis. There might not be enough AAA rated bonds in the U.S. treasury market to calculate the index.

sovereign default risks, with the risk premia accounting for an even larger component of the sovereign spreads.

Based on this discussion, it is safe for us to argue that sovereign credit spreads are driven by the level of sovereign risks as well as the prices for bearing 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 a lot over time. So in this section, we also include the global risk premiums as one of the explanatory variables in our regression 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 US markets to represent global variables.

*Equity Risk Premium* - Similar to Longstaff et al. (2007), we use the the earnings-price (E/P) ratio of S&P 500 Index as a proxy for equity risk premium[2]. Although "admittedly simplistic", the changes in this E/P ratio do reflect the 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 simply calculate the changes in expected excess return on five-year U.S. Treasury bonds based on the linear model used in Cochrane and Piazzesi (2002). Specifically speaking, 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 the estimated parameters of the single-factor model based on Fama-Bliss data in their paper. 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 get monthly changes in bond risk premium.

[2]Longstaff et al. (2007) used the E/P ratio and other data for S&P 100 Index in calculating risk premiums. However, to be consistent with the VIX index in this section, we use the data of S&P 500 Index instead.

*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 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 asset price levels, but also the components of uncertainty in future volatilities. VRP can simply be 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 as:

$$\begin{aligned} VRP &= (\text{Implied Volatility})^2 - (\text{Realized Volatility})^2 \\ &= \text{Implied Variance} - \text{Realized Variance}. \end{aligned} \tag{4.1}$$

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 theorists, 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 can be calculated as:

$$\text{Implied Variance} = (\frac{VIX}{100})^2 \tag{4.2}$$

The realized volatility plays an important and practical role in derivative pricing and portfolio risk management (Merton and Samuelson, 1990). The primary method to estimate the realized volatility is based only on the close-to-close prices. To achieve better accuracy, sophisticated estimators are 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 need to introduce the following notations [3]:

$f$: fraction of the period (interval [0,1]) that trading is closed;

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

$V$: unknown variance of price change, namely $\sigma^2$;

$C_0$: closing price of previous period (at time 0);

$C_1$: closing price of current period (at time 1);

$O_1$: opening price of 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;

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

$$V_{cc} = \frac{1}{n-1}\sum_{i=1}^{n}[(o_i + c_i) - \frac{1}{n}\sum_{i=1}^{n}(o_i + c_i)]^2 \tag{4.3}$$

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

$$V_P = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{4ln2}(u_i - d_i)^2. \tag{4.4}$$

Another variance estimator using high-low-close prices was developed by Rogers and Satchell (1991) as:

$$V_{RS} = \frac{1}{n}\sum_{i=1}^{n}[u_i(u_i - c_i) + d_i(d_i - c_i)]. \tag{4.5}$$

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

$$V_{GK} = \frac{1}{n}\sum_{i=1}^{n}o_i^2 - 0.383\frac{1}{n}\sum_{i=1}^{n}c_i^2 + 1.364V_P + 0.019V_{RS}. \tag{4.6}$$

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

$$V_{YZ} = V_O + kV_C + (1-k)V_{RS}, \tag{4.7}$$

where

$$V_O = \frac{1}{n-1}\sum_{i=1}^{n}(o_i - \frac{1}{n}\sum_{i=1}^{n} o_i)^2, \tag{4.8}$$

$$V_C = \frac{1}{n-1}\sum_{i=1}^{n}(c_i - \frac{1}{n}\sum_{i=1}^{n} c_i)^2, \tag{4.9}$$

$$k = \frac{\alpha - 1}{\alpha + \frac{n+1}{n-1}}, \tag{4.10}$$

with $\alpha$=1.34 in practice.

As Yang and Zhang (2000) illustrated, their estimator has several advantages over other methods: it is unbiased and independent of both the drift and opening jumps, and it has the minimum variance and highest efficiency among estimators with similar properties. Thereby we use the estimator in Equation (4.7) to compute the realized volatility[4].

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)[5] estimator of the realized volatility on the high, low, open and close prices of S&P 500 Index. Then the annualized volatility risk premium is computed as:

$$\begin{aligned} VRP &= \text{Implied Variance} - \text{Realized Variance} \\ &= (\frac{VIX}{100})^2 - 252V_{YZ}. \end{aligned} \tag{4.11}$$

### 4.1.4 Regional Sovereign Spreads

The correlation matrices and PC analysis results in Chapters 2 3 show the relatively close correlations between sovereign credit spreads of countries from the same geographic

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

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

region, and indicate the potential impact of regional factors on sovereign CDS spreads. As a proxy for the underlying regional factor, we also include certain measures of regional sovereign spreads in the regression.

To be specific, since all of the countries studied in this thesis come from either Asia or Europe, the two variables are named as Asian Spread and 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 regression, because there are double counted information contained in the regional spreads and other variables, such as the shocks of global economic variables. To eliminate this double counting information and represent the regional impact more accurately, further steps are implemented. Simply we regress 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, which represent the additional regional variables.

## 4.2 Regression Analysis

For each of the eight countries studied in this thesis, we regress the monthly changes of their sovereign CDS spreads on the local and global variables. The regression results, which consist of the t-statistics for each explanatory variable based on the autocorrelation and heteroskedasticity consistent covariance matrix estimates[6] of Newey and West (1987)

[6]Longstaff et al. (2007) reported the t-statistics based on heteroskedasticity consistent covariance matrix estimates of White (1980). However we argue that autocorrelation would also be an issue in the regression, thereby we use autocorrelation and heteroskedasticity consistent covariance matrix estimates

and the adjusted $R^2$ for each regression, are shown in Table 6. In addition to them, 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 get the $R^2$ of this regression; then we 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 is more likely to be an upper bound for the proportion (Longstaff et al., 2007).

of Newey and West (1987) instead.

**Table 4.1:** 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** | | | | | | | | |
| Asia Region | 7.611** | 2.227** | 3.695** | 1.081 | 3.300** | 4.423** | 4.910** | -1.616 |
| Europe 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 |
| **Adjust-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, the adjusted $R^2$s are generally high: Except that the regression for Germany has a relative low adjusted $R^2$ of 35.1%, and the regression for Japan has a moderate one of 48.8%, all the $R^2$s of other regressions are larger than 65%. This demonstrates that those regression variables capture most of the variations in the sovereign CDS spreads. The mean and median values of the adjusted $R^2$s are 66.1% and 70.1% respectively.

Actually, the adjusted $R^2$s are unexpectedly high, since we are regressing changes in variable on changes in a set of covariates. To test the influences of the omitted long-run frequency information, we test these regressions by adding a time trend to our expeditionary variables. However, the adjusted $R^2$s are only slightly reduced (less than 1%) with the time trend covariate added. Another possible explanation for these spuriously high adjusted $R^2$s is the presence of common trends among the covariates. After we check the plots of these covariates, it is clear that the high adjusted $R^2$s partly due structural changes over the sample period.

Turning now to the local variables, the results in Table 4.1 indicate the local economy has strong influences on sovereign credit risk. The local stock markets are significant at the level of 5% for six of the eight countries, and all their coefficients are negative. Accordingly, a bad performance in the local stock market contributes to the increased sovereign credit risk. The exchange rate is also an important explanatory variable, with coefficients significant at 10% for five countries. Similar to those of the local stock markets, the coefficients of the exchange rates are almost negative, indicating the appreciation of the local currency against the US dollar has a positive effects on the reduction of sovereign credit risk.

The foreign reserve is likewise important in explaining the changes of sovereign CDS spreads. Half of these coefficients are statistically significant at 5%. All of the European countries have negative coefficients for foreign reserves, while Asian countries have positive ones. On one hand, for developed countries, such as all of the selected European countries in this thesis, their foreign reserves are kept at a relatively low level for the long term. An increase in their foreign reserves signals that they can better service their foreign debt obligations, thus results in decreased sovereign CDS spreads.

On the other hand, for the emerging markets, people have noticed the large-scale use as well as the sizable accumulation of foreign exchange reserves, especially in Asia(Mohanty and Turner, 2006; Pineau et al., 2006). As Fukuda and Kon (2008) reported, when these developing countries increase their foreign exchange reserves, the liquid debt and total debt increase as well. They also provided cross-country empirical evidence of increased foreign exchange reserves leading to outstanding larger external debt. This has caused and deepened investors' concerns about the state of economies in these emerging markets. As a result, the foreign reserve has reverse effects on sovereign credit spreads in Asian countries compared with European ones.

The ratios for 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%. And the mean and median values are 55.7% and 60.6%. Thereby, the explanation power of the local variables varies significantly across countries. On average, the local variables can explain about 56% of the variation of sovereign credit risk at maximum.

As for the global financial market variables, the regression results are quite intriguing. The most significant variables in this part are global stock market returns. For all of the selected countries, the global stock market variables are significant for five countries at 10%. Strictly speaking, the coefficients of the global stock market return for all of the Asian countries are negative, while those of most of the European countries are positive. This implies that there may exist reverse effects of global stock markets on sovereign credit risk in different regions.

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

The ratios for 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 local economy, global financial markets have effects on sovereign credit risk to the similar extent.

The ratios for global risk premiums range from 24.0% to 71.5%, with mean value of

47.7% and 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 sovereign credit risk: The equity risk premium is significant for France, Germany, and Philippines at 5%; the volatility risk premium is significant for China, Korea, and Philippines at 5%; and the treasury risk premium is significant for China and Philippines at 5%.

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

Finally, the results for the regional spreads show that, even after we include all of these local and global variables in the regression, there are still strong associations between sovereign credit spreads. However the ratios for 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 explanatory power of the regional spread variables cannot be depreciated. The Asian region spread is significant for all of the Asian countries plus France at 5%, while the Europe region spread is significant for most of the European countries.

In general, these regional spread variables can be viewed as the regional or global factors that have influences on sovereign credit risk, while these influences are not captured by other explanatory variables. One of the possibilities is the related liquidity factor (Longstaff et al., 2007). We notice again that, the signs of coefficients for some variables such as the foreign reserve, the global stock , and the volatility risk premium are opposite for most of the European and Asian countries. This further reinforces the importance of certain regional factors that are not listed above.

# Chapter 5

# Pricing Model

As Pan and Singleton (2008) mentioned, the basic pricing principle of sovereign CDS contracts is similar to that of corporate CDS contracts. Based on this argument, we introduce the model to price sovereign CDS spread in this chapter.

## 5.1 The Model

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

$$\frac{1}{2}CDS_t(M)\sum_{j=1}^{2M} E_t^{\mathbb{Q}}\left[e^{-\int_t^{t+.5j}(r_s+\lambda_s^{\mathbb{Q}})ds}\right] = (1-R^{\mathbb{Q}})\int_t^{t+M} E_t^{\mathbb{Q}}\left[\lambda_u^{\mathbb{Q}} e^{-\int_t^{u}(r_s+\lambda_s^{\mathbb{Q}})ds}\right]du, \quad (5.1)$$

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; $\lambda_t$ is the risk-neutral intensity of default, i.e. the intensity of arrival rate of a credit event. To fix notation, in this thesis, 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 distributions.

As Pan and Singleton (2008) explained, the left hand side of Equation (5.1) 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 $\lambda_t$ and $r_t$ are independent, the arbitrage-free price of a standard sovereign CDS contract with M years maturity at issue can be written as:

$$\begin{aligned} CDS_t(M) &= \frac{2(1-R^{\mathbb{Q}})\int_t^{t+M} E_t^{\mathbb{Q}}\left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u (r_s+\lambda_s^{\mathbb{Q}})ds}\right]du}{\sum_{j=1}^{2M} E_t^{\mathbb{Q}}\left[e^{-\int_t^{t+.5j}(r_s+\lambda_s^{\mathbb{Q}})ds}\right]} \\ &= \frac{2(1-R^{\mathbb{Q}})\int_t^{t+M} D(t,u) E_t^{\mathbb{Q}}\left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u \lambda_s^{\mathbb{Q}}ds}\right]du}{\sum_{j=1}^{2M} D(t,t+j/2) E_t^{\mathbb{Q}}\left[e^{-\int_t^{t+.5j}\lambda_s^{\mathbb{Q}}ds}\right]}, \end{aligned} \tag{5.2}$$

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 of Pan and Singleton (2008), it is appropriate to [1] to treat $L^{\mathbb{Q}}$ as a constant parameter, and assume that there is no risk premium on recovery, namely $L^{\mathbb{Q}} = L^{\mathbb{P}}$.

Turning now to the risk-neutral intensity of a credit event $\lambda^{\mathbb{Q}}$, the literature usually assume that $\lambda_u^{\mathbb{Q}}$ follows one of the following three models: the square-root diffusion such as the Cox-Ingersoll-Ross (CIR) model (Zhang, 2003; Longstaff et al., 2005); the "three-halves" diffusion (Ahn and Gao, 1999); or $ln(\lambda^{\mathbb{Q}})$ follows an Ornstein-Uhlenbeck process (Berndt et al., 2004; Pan and Singleton, 2008; Longstaff et al., 2007).

Here in this thesis, we adopt the assumption of the CIR model for the following reasons: first, the CIR model assures $L^{\mathbb{Q}}$ to be non-negative and mean-reverting, which is consistent with its definition intuitively; second, using the CIR model, we can get closed-

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

form solutions for the expectations in the numerator and denominator of Equation (5.2), which simplifies our calculation and optimization.

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

$$d\lambda_t^{\mathbb{Q}} = \kappa^{\mathbb{P}}(\theta^{\mathbb{P}} - \lambda_t^{\mathbb{Q}})dt + \sigma_\lambda \sqrt{\lambda_t^{\mathbb{Q}}} dB_t^{\mathbb{P}}, \tag{5.3}$$

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

$$d\lambda_t^{\mathbb{Q}} = \kappa^{\mathbb{Q}}(\theta^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})dt + \sigma_\lambda \sqrt{\lambda_t^{\mathbb{Q}}} dB_t^{\mathbb{Q}}. \tag{5.4}$$

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

$$\eta_t = \frac{\delta_0 + \delta_1 \lambda_t^{\mathbb{Q}}}{\sqrt{\lambda_t^{\mathbb{Q}}}}, \tag{5.5}$$

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 standard CIR model, we can calculate the following elements:

$$E_t\big[\exp\big(\beta \int_t^s \lambda_u du\big)\big] = A(\beta, \tau) e^{B(\beta,\tau)\lambda_t}, \tag{5.6}$$

$$E_t\big[\lambda_s \exp\big(\beta \int_t^s \lambda_u du\big)\big] = \big[C(\beta, \tau) + D(\beta, \tau)\lambda_t\big] e^{B(\beta,\tau)\lambda_t}, \tag{5.7}$$

for any $\beta$, where $\tau = s - t$ and

$$\phi = \sqrt{-2\beta\sigma^2 + \kappa^2}, \tag{5.8}$$

$$\gamma = \frac{\kappa + \phi}{\kappa - \phi}, \tag{5.9}$$

$$A(\beta, \tau) = \exp\big(\frac{\kappa\theta(\phi + \kappa)}{\sigma^2}\tau\big)\big(\frac{1-\gamma}{1 - \gamma e^{\phi\tau}}\big)^{\frac{2\kappa\theta}{\sigma^2}}, \tag{5.10}$$

$$B(\beta, \tau) = \frac{\kappa - \phi}{\sigma^2} + \frac{2\phi}{\sigma^2(1 - \gamma e^{\phi\tau})}, \tag{5.11}$$

$$C(\beta, \tau) = \frac{\kappa\theta}{\phi}(e^{\phi\tau} - 1)\exp\big(\frac{\kappa\theta(\phi + \kappa)}{\sigma^2}\tau\big)\big(\frac{1-\gamma}{1 - \gamma e^{\phi\tau}}\big)^{\frac{2\kappa\theta}{\sigma^2}+1}, \tag{5.12}$$

$$D(\beta, \tau) = \exp\big(\frac{\kappa\theta(\phi + \kappa) + \phi\sigma^2}{\sigma^2}\tau\big)\big(\frac{1-\gamma}{1 - \gamma e^{\phi\tau}}\big)^{\frac{2\kappa\theta}{\sigma^2}+2}. \tag{5.13}$$

Here in this thesis, according to Equation (5.2), we set $\beta = 1$ for the calculation of these expectations.

## 5.2 Maximum Likelihood Estimation

In this section, we apply this pricing model to sovereign CDS spreads and estimate the parameters in the model using maximum likelihood (MLE) method. As Longstaff et al. (2007) mentioned, to estimate all these parameters mentioned above, we need to construct a term structure of CDS spreads for each sovereign.

For this purpose, we collect one-year and three-year sovereign CDS data for selected countries from September 2004 to December 2011[2]. Now for these countries, we have a term structure of one-year, three-year, and five-year sovereign CDS contracts. Similarly to Longstaff et al. (2007), parameters are estimated via the MLE method using the conditional distribution of the observed spreads implied by the non-central chi-square distribution of $\lambda$.

We also assume there is no pricing error for the three-year contract, while the one-year and five-year contracts have pricing errors, which follow the normal distribution with mean zero and standard deviation $\sigma_\varepsilon(1)$ and $\sigma_\varepsilon(5)$ respectively[3]. Longstaff et al. (2007) 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 the five-year contracts. They found that based on the assumption and the CDS term structure, the pricing error $\sigma_\varepsilon(M)$ "tend to be smaller for the intermediate maturities".

Besides, as discussed, the recovery rate $R^{\mathbb{Q}}$ is set to be 0.25. The present value

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

[3]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 Bloomberg data base. Intuitively, we assume the three-year contract has no pricing error.

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 Maximum Likelihood, we provide the following details:

For a CIR process

$$d\lambda_t = \kappa(\theta - \lambda_t)dt + \sigma\sqrt{\lambda_t}dB_t, \tag{5.14}$$

if $\kappa$, $\theta$, $\sigma$ are all positive, and $2\kappa\theta > \sigma^2$ holds, this process has a steady marginal distribution.

Given $\lambda_t$ at time $t$, the density of $\lambda_{t+\Delta t}$ is

$$p(\lambda_{t+\Delta t}|\lambda_t;\kappa,\theta,\sigma,\Delta t) = ce^{-u-v}(\frac{v}{u})^{\frac{q}{2}}I_q(2\sqrt{uv}), \tag{5.15}$$

where

$$c = \frac{2\kappa}{\sigma^2(1-e^{-\kappa\Delta t}}), \tag{5.16}$$

$$u = c\lambda_t e^{-\kappa\Delta t}, \tag{5.17}$$

$$v = c\lambda_{t+\Delta t}, \tag{5.18}$$

$$q = \frac{2\kappa\theta}{\sigma^2} - 1, \tag{5.19}$$

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

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

$$\begin{aligned}\ln L(\kappa,\theta,\sigma) &= \sum_{i=1}^{N-1} \ln p(\lambda_{t+\Delta t}|\lambda_t;\kappa,\theta,\sigma,\Delta t) \\ &= (N-1)\ln c + \\ &\quad \sum_{i=1}^{N-1}\big[-u_{t_i} - v_{t_{i+1}} + 0.5qln(\frac{v_{t_{i+1}}}{-u_{t_i}}) + \ln(I_q(2\sqrt{v_{t_{i+1}}u_{t_i}}))\big].\end{aligned} \tag{5.20}$$

By maximizing the log-likelihood function, namely Equation (5.20), we can obtain the maximum likelihood estimates of parameters $\hat{\kappa}$, $\hat{\theta}$, and $\hat{\sigma}$.

For solving this optimization problem, we can do a simple transition:

$$\begin{aligned}(\hat{\kappa}, \hat{\theta}, \hat{\sigma}) &= \arg \max_{(\kappa,\theta,\sigma)} \ln L(\kappa, \theta, \sigma) \\ &= \arg \min_{(\kappa,\theta,\sigma)} \big\{ - \ln L(\kappa, \theta, \sigma)\big\}, \end{aligned} \tag{5.21}$$

and then rely on 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 under 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 Estimation Test

Before MLE method is used to estimate these parameters and price 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 $\lambda$ for the same length of the sample period[4] using a Monte Carlo method. Then we can get 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 MLE 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.

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

The test results are reported in Table 5.1. The average value of the total pricing error for the simulated data is only 0.2813% with the standard deviation value of 0.0175%. Thus, the sovereign credit model with estimated parameters via MLE method can price the data precisely. We notice that the model prices the three-year contracts perfectly with zero pricing error. For the five-year data, the average value of the pricing error is only 0.1567%, which is also 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 related to the term structure of contracts in this pricing model, especially when the model is used to price the one-year contracts.

**Table 5.1:** Estimation Test Results[1]

| | **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 is calculated with 100 simulation runs. Here are the initial values of underlying parameters: $\kappa^{\mathbb{Q}} = 0.045$, $\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}} = 0.022$,$\sigma_\lambda = 0.028$, $\kappa^{\mathbb{P}} = 0.55$, $\kappa^{\mathbb{P}}\theta^{\mathbb{P}} = 0.055$.

## 5.4 Estimation Results for the Full Sample Period

The above test shows that MLE method could help us evaluate quite accurately the data under the square-root model. So here in this part, we adopt it to the real world data for the full sample period. Our focus is on a subset of sovereigns, which include China, Germany, Italy, Korea, and Philippines. France, Japan, and Spain are excluded from the data set because there was not enough sovereign CDS term structure data available. As mentioned, the sample period is set to be September 2004 to December 2011 for the five countries limited to data availability.

Table 5.2 reports the maximum likelihood estimates for parameters in 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 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 the average value of 20.34% and median value of 18.36%. For the one-year contracts, the pricing errors range from 16.00% to 73.89%, with the average value of 42.03% and median value of 36.77%.

**Table 5.2:** MLE Parameters Estimates for Sovereign Credit Risk[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 |
| $\sigma_\lambda$ | 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 |

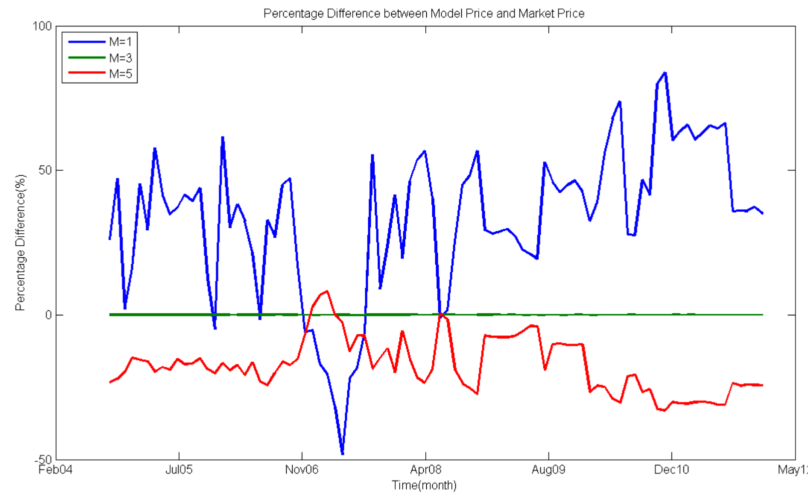
[1] The sample data are monthly sovereign CDS spreads for the period from September 2004 to December 2011.

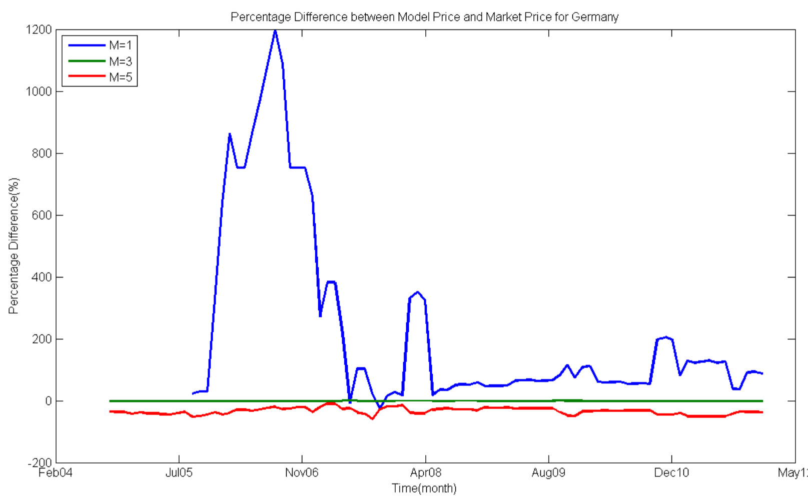
[2] All the pricing error in percentage mentioned in this table are calculated as the absolute differences between model price and market price over the market price.

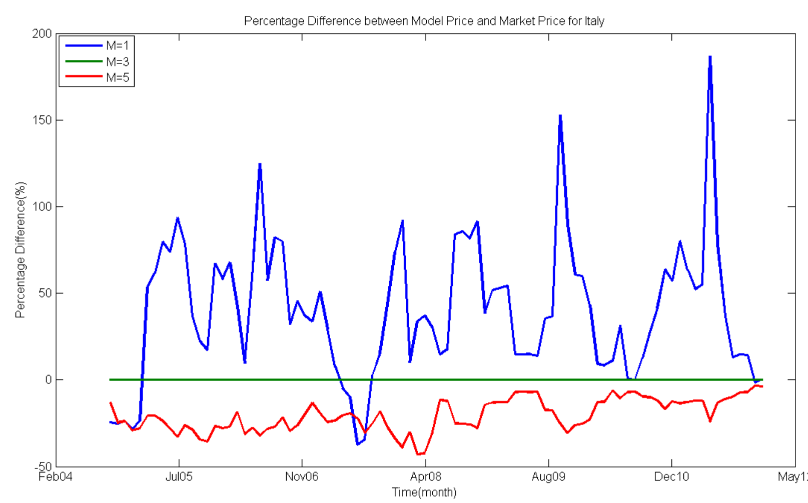
For each row of the absolute pricing errors in percentage, we see that the ranking of the five countries is consistent. That is, Korea has the smallest pricing error in percent, while Germany has the largest. For each column, i.e for each sovereign, the percent error for the one-year contract is always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


Percentage Difference between Model Price and Market Price
M=1
M=3
M=5
Percentage Difference(%)
100
50
0
-50
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12
Time(month)


Percentage Difference between Model Price and Market Price for Germany
M=1
M=3
M=5
Percentage Difference(%)
1200
1000
800
600
400
200
0
-200
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12
Time(month)


Percentage Difference between Model Price and Market Price for Italy
M=1
M=3
M=5
Percentage Difference(%)
200
150
100
50
0
-50
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12
Time(month)

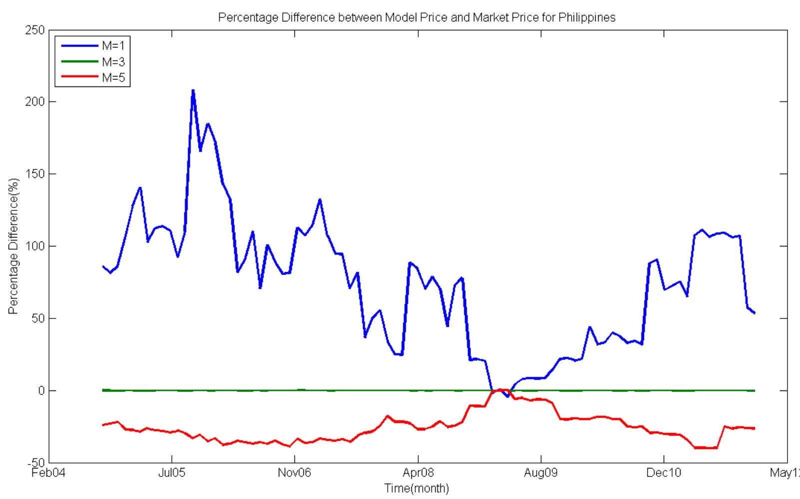




**Figure 5.1:** Percentage Difference between Model Price and Market Price

sovereign bonds".

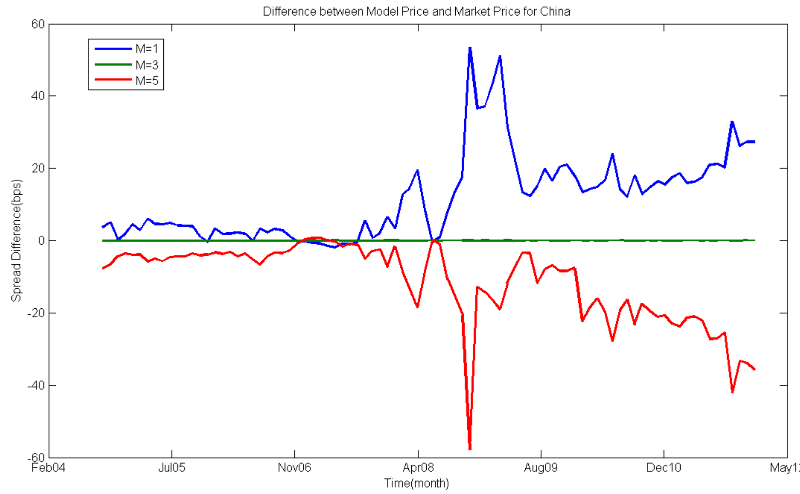
Second, the accuracy of our sovereign credit risk model varies greatly from country to country. Among all of these countries, Germany has the largest pricing error, 31.81%. Recall that in our regression analyses, the adjusted $R^2$ of Germany is only 15.3%, which is much less than those of other countries. That is, when the variance in 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 a small extent. Reasonably, a large parts of components of Germany's CDS curves are not captured by the one-factor model. More factors may be introduced in the model to increase its pricing accuracy for Germany.

These pricing errors in percentage reported in Table 5.2 are all calculated as absolute values. Now we also want to take a look at the real values of pricing error in percentage[5], which are plotted in Figure 5.1 for the five sovereigns respectively. The three-year contracts are priced perfectly, which can be used an a benchmark.

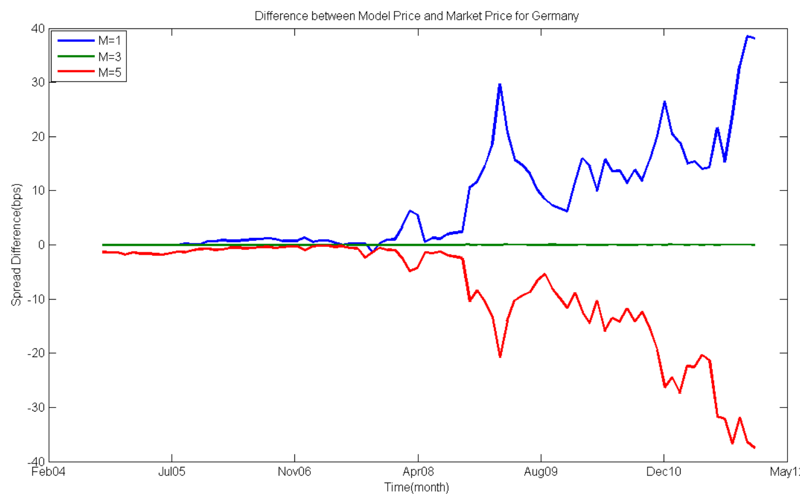
As shown, most of the times, for all of the sovereigns, the model prices for one-year contracts are overestimated, while the model prices for five-year contracts are underestimated. This finding is consistent with the results of Pan and Singleton (2008) and Longstaff et al. (2007). We argue that this is due to the natural drawbacks of our one-factor credit risk model based on the CDS term structure. Meanwhile, the region of pricing errors for one-year contracts is obviously larger than that for five-year contracts, consistent with the results of pricing errors reported in Table 5.2. According to Pan and Singleton (2008), a possible explanation for this anomalous behavior of one-year contract is "the liquidity or supply/demand premium".

There are also some intriguing findings on the estimates of underlying parameters. Values of $\sigma_\varepsilon(1)$ are no less than values of $\sigma_\varepsilon(5)$ for all the sovereigns. As discussed earlier, the short ends of the CDS curves are less well captured by our one-factor model compared

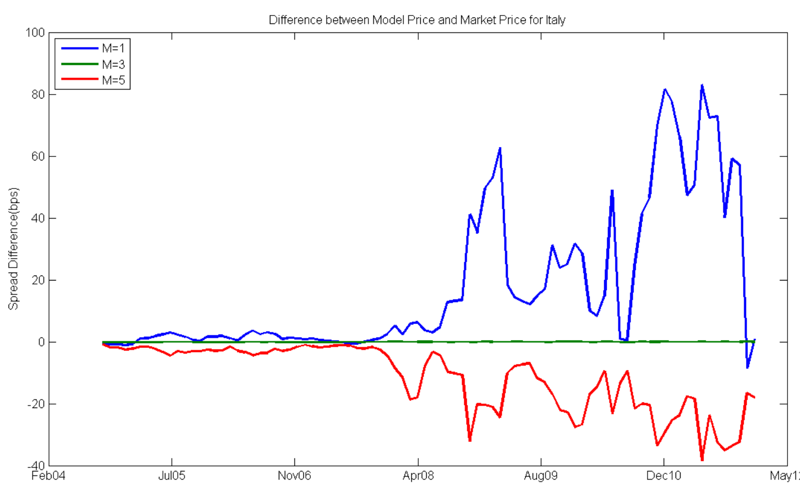
[5]For each month, the numerator is calculated by subtracting market price from model price, and the denominator is the market price



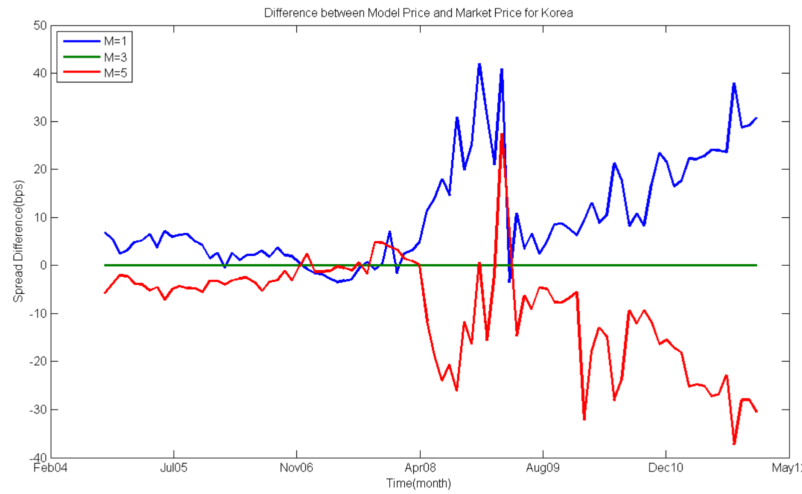
Difference between Model Price and Market Price for China
M=1
M=3
M=5
Spread Difference(bps)
60
40
20
0
-20
-40
-60
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12
Time(month)

Difference between Model Price and Market Price for Germany
M=1
M=3
M=5
Spread Difference(bps)
40
30
20
10
0
-10
-20
-30
-40
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12
Time(month)

Difference between Model Price and Market Price for Italy
M=1
M=3
M=5
Spread Difference(bps)
100
80
60
40
20
0
-20
-40
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12
Time(month)



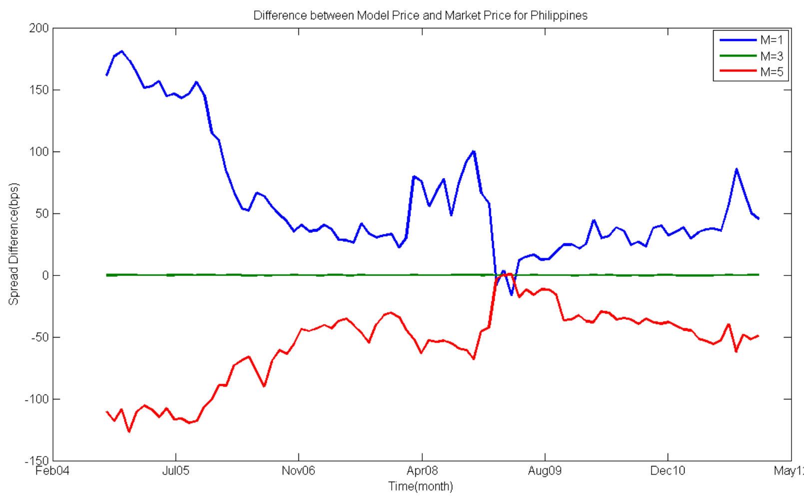




**Figure 5.2:** Difference between Model Price and Market Price

with the five-year contracts. Thus larger volatility of the model pricing error $\varepsilon$ for one-year contract is actually expected.

The median values for them are 17 and 16 basis points respectively. Similar to the conclusions of Longstaff et al. (2007), this volatility is acceptable from a percentage perspective, considering that the sovereign spreads can go up to hundreds of basis points in Table 2.2.

Finally, we plot the difference between model price and market price in basis points in Figure 5.2. Similarly, the difference for three-year contracts are zero and can be regarded as a benchmark. The underestimation tendency for five-year contracts and overestimation tendency for one-year contracts are also visible in this case. Another noticeable feature is that, except for Philippines, there are only minor differences around zero in basis points between the model price and market price for other sovereigns before April 2008. Nevertheless, these differences rose to a much larger level after that time.

Therefore, the 2008-2009 financial crisis is seen as a turning point for our credit risk model. Before the financial crisis, the performance of the model is actually quite ideal. This contrast reminds us of the PC analysis results presented in Table 3.2, where we also noticed a large difference between the analysis results before and after the financial crisis. Based on all of these analyses and observations, it would be unreasonable for us to price the sovereign credit risk using the same estimates of underlying parameters for the entire sample period.

Intuitively, after the 2008-2009 financial crisis and the Euro debt crisis, there should be 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 period and post-crisis period separately.

## 5.5 Estimation Results for Pre-crisis Period and Post-crisis Period

As discussed, now we divide the entire period into a pre-crisis period, which lasts from September 2004 to August 2008, and a post-crisis period, which lasts from September 2008 to December 2011, and then use the MLE method to estimate the parameters for each period separately. The absolute pricing errors in percentage using MLE for two subsample periods (the percentage is calculated based on the data for the full sample period) are reported in Table 5.3. The resulting estimation results are reported in Table 5.4.

**Table 5.3:** 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 |

More specifically, compared with the results in Table 5.2, the total absolute pricing errors in Table 5.3 using estimates for two subsample periods are substantially reduced. The mean of total pricing error is reduced from the previous value of 18.36% to the value of 13.47%, with standard error and median reduced as well. Now the total pricing errors in percentage range from 8.13% to 20.07%, which are acceptable considering the limits of the one-factor model. Meanwhile, most of the pricing errors in percentage for one-year and five-year contracts decrease as well. In general, using estimates of parameters from subsamples improves the performance of our credit risk pricing model notably.

**Table 5.4:** MLE Parameters Estimates for Pre-crisis Period vs Post-crisis Period

| Time Period | Parameters | China | Germany | Italy | Korea | Philippines | Mean | SD | Median |
|---|---|---|---|---|---|---|---|---|---|
| Sept 2004 - Aug 2008 | $\kappa^{\mathbb{Q}}$ | 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 |
| | $\sigma_\lambda$ | 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 |
| | $\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$ | 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 |
| Sept 2009 - Dec 2011 | $\kappa^{\mathbb{Q}}$ | 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 |
| | $\sigma_\lambda$ | 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 |
| | $\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$ | 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 detailed estimates of the parameters in Table 5.4, we see largely different values of parameters before and after the crisis.

For example, the pricing errors $\sigma_\varepsilon(1)$ and $\sigma_\varepsilon(5)$ tend to differ from zero much more 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. And it reflects CDS data are more turbulent in the post-crisis period.

Meanwhile, we notice that the absolute pricing errors are reduced to different extents after the crisis. This indicates that our pricing model provides a better fit to the sovereign CDS market data after the crisis.

Here we do not want to spend too much effort on the detailed comparison of $\kappa$, $\kappa\theta$, and $\sigma_\lambda$ in the historical and risk-neutral distributions. In a word, the estimates of these parameters vary in a large scale from country to country before the crisis. Nevertheless, their ranges decrease to a smaller scale after the crisis.

To summarize, the MLE for the pre-crisis and post-crisis periods provides a better and more reasonable estimates of the underlying parameters. Consequently, our one-factor square-root diffusion model delivers a more accurate pricing of the sovereign's CDS spreads.

# Chapter 6

# Components of CDS Spreads

Following Pan and Singleton (2008) and Longstaff et al. (2007), we now analyze and decompose the sovereign credit risk into distress risk premium and credit-event components in this chapter.

## 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 of higher default (or other credit events) probability, investors will ask for a compensation, which is the distress risk premium that we focus on.

As discussed, 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.

Suggested by Pan and Singleton (2008), given the arrival rates of credit events and its governing parameters under the historical distribution $\mathbb{P}$, we now can calculate the credit-event components as:

$$CDS_t^{\mathbb{P}}(M) \quad = \quad \frac{2(1-R^{\mathbb{Q}})\int_t^{t+M} D(t,u)E_t^{\mathbb{P}}\left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u \lambda_s^{\mathbb{Q}} ds}\right] du}{\sum_{j=1}^{2M} D(t,t+j/2)E_t^{\mathbb{P}}\left[e^{-\int_t^{t+.5j} \lambda_s^{\mathbb{Q}} ds}\right]}. \tag{6.1}$$

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

$$RP(\text{Risk Premium}) = CDS_t(M) - CDS_t^{\mathbb{P}}(M). \tag{6.2}$$

Based on Equations (6.1) and (6.2), we can also evaluate the fractional influences or weights of risk premium components in total CDS spreads as:

$$WRP(\text{Weights of Risk Premium}) = \frac{CDS_t(M) - CDS_t^{\mathbb{P}}(M)}{CDS_t(M)}. \tag{6.3}$$

## 6.2 Risk Premium Analyses

Based on the estimated parameters[1], we calculate the risk premium and credit-event components for five-year sovereign CDS contracts[2].

Table 6.1 provides us the descriptive statistics about risk premium components and weights of risk premium components embedded in five-year sovereign CDS contracts. From this table, we see drastic differences in 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 potential of systematic risks in the post-crisis period for European countries. And the Euro debt crisis aggravates this state of the economy and raises global concerns.

[1]Here we use the estimates of parameters from subsamples in Table 5.4, because our model performs a more accurate pricing under these values.

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

**Table 6.1:** Descriptive Statistics for Risk Premiums and Weights of Risk Premiums

| | Risk Premiums (bps) | | | Weights of Risk Premiums (%) | | |
|---|---|---|---|---|---|---|
| Country | 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 |

Figure 6.1 plots the decomposition of the five-year sovereign CDS contracts below. For each sovereign, the market price, model price, risk premium components, and credit-event components are shown using different colors for each country. First, for all of the five countries, the market price line and model price line match with each other, implying that our model could price the sovereign credit risk precisely.

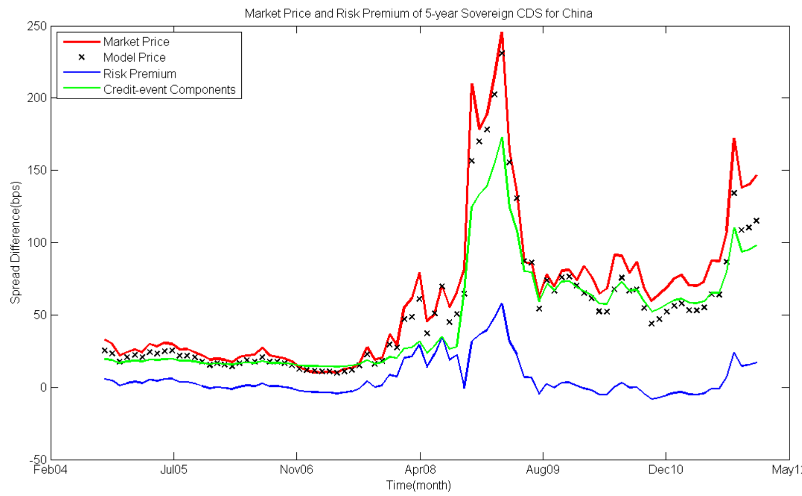
Second, the distributions of the CDS spreads and components for Asian countries vary greatly compared with those for European countries. As shown, for Asian countries, all of these components and prices remain at a relative low level before the 2008-2009 financial crisis[3], and reach the peak during the crisis period. Comparing their risk premiums with credit-event components, apparently 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. So in a long term, investors mainly place their concerns on the possibility of credit events rather than systematic risks.

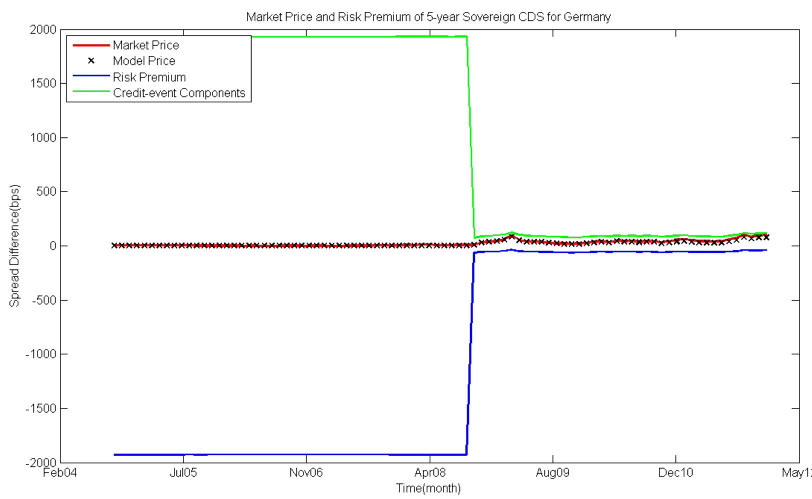
As for European countries, for the pre-crisis period, both Italy and Germany have CDS spreads approximating zero. They also have large pricing errors of 67.30% and 37.81%, shown in Table 5.3, that can not be ignored. We argue that these leads to the evaluation inaccuracy of risk premium and credit-event components in the two countries.

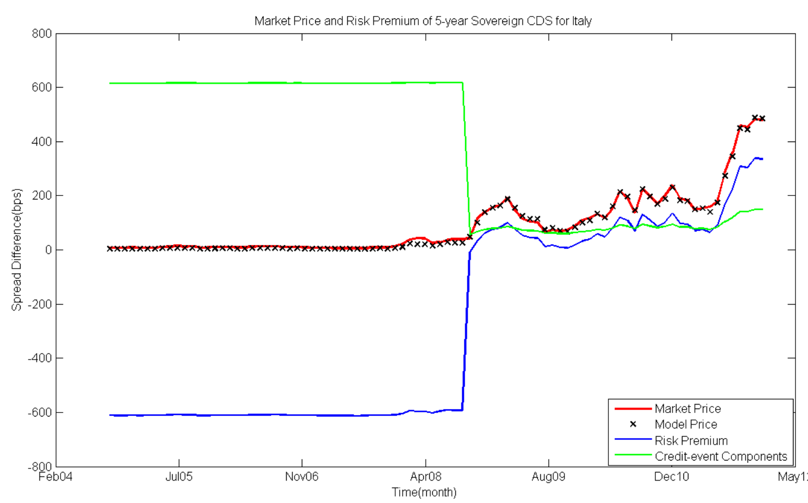
In addition, we provide the plots of weights for risk premiums for one-year, three-year,

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

and five-year contracts for each sovereign in Figure 6.2. Despite the differences between the plots for different countries, for the same country, the distributions for contracts with different maturities tend to cluster together. Another noticeable feature is that the weights of 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 6.1 that credit-event components weight much more than risk-premiums for most countries.


Market Price and Risk Premium of 5-year Sovereign CDS for China
Market Price
Model Price
Risk Premium
Credit-event Components
Spread Difference(bps)
250
200
150
100
50
0
-50
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12
Time(month)


Market Price and Risk Premium of 5-year Sovereign CDS for Germany
Market Price
Model Price
Risk Premium
Credit-event Components
Spread Difference(bps)
2000
1500
1000
500
0
-500
-1000
-1500
-2000
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12
Time(month)


Market Price and Risk Premium of 5-year Sovereign CDS for Italy
Market Price
Model Price
Risk Premium
Credit-event Components
Spread Difference(bps)
800
600
400
200
0
-200
-400
-600
-800
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12
Time(month)

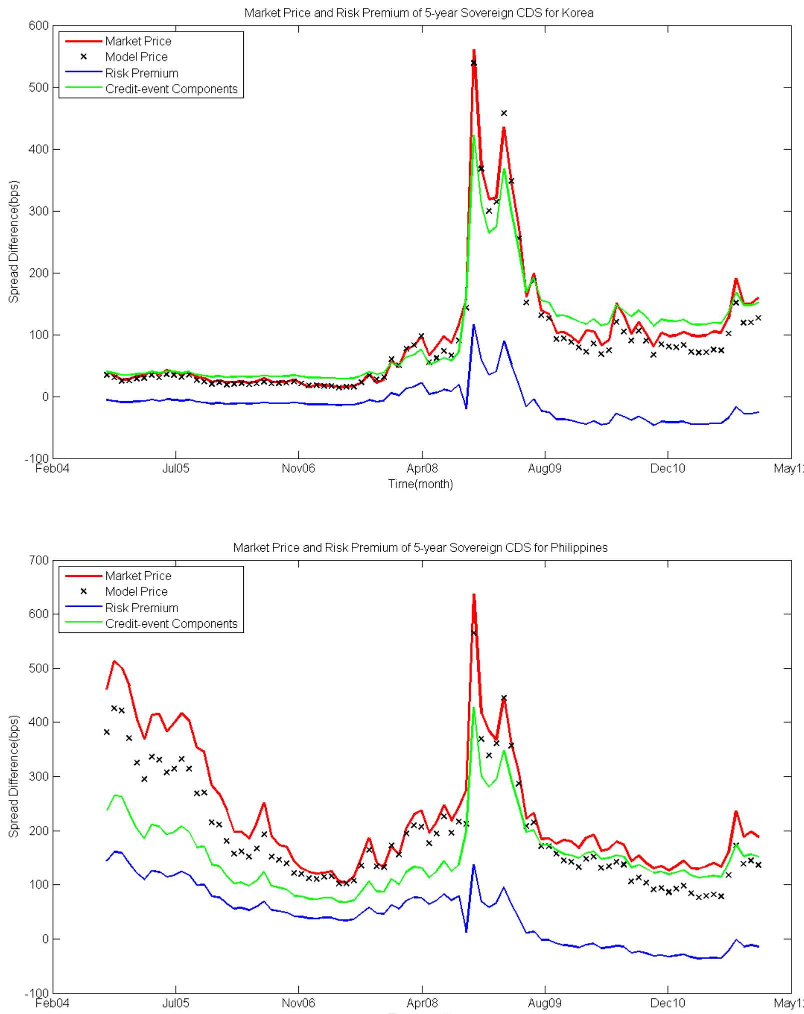
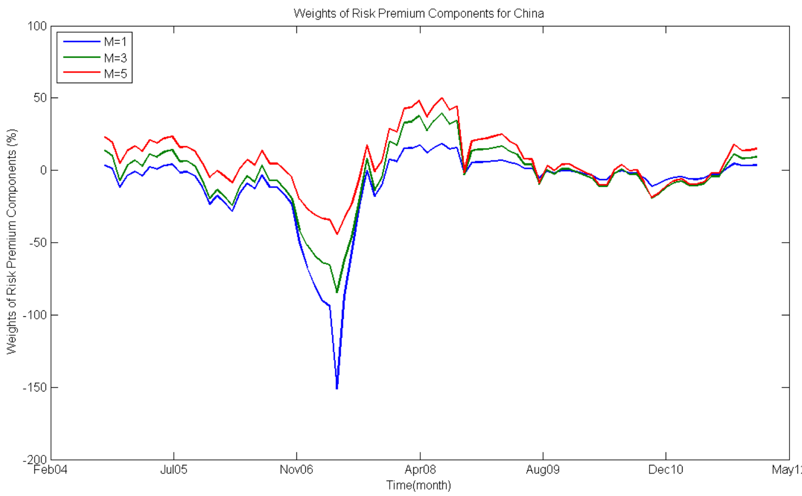
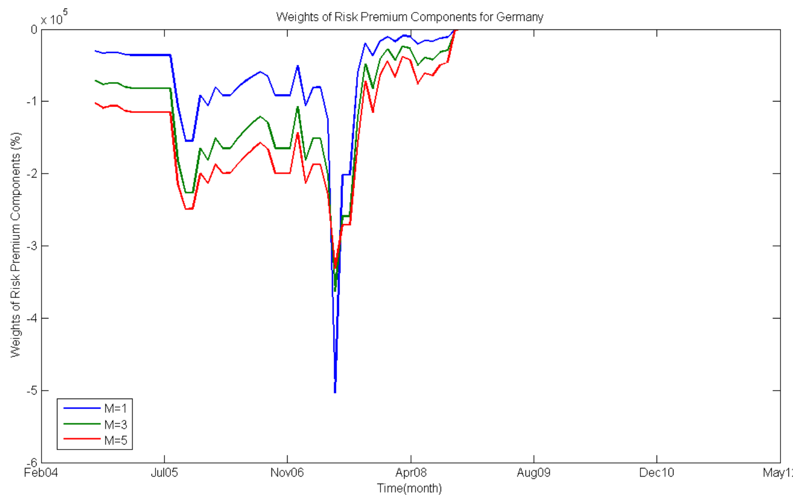


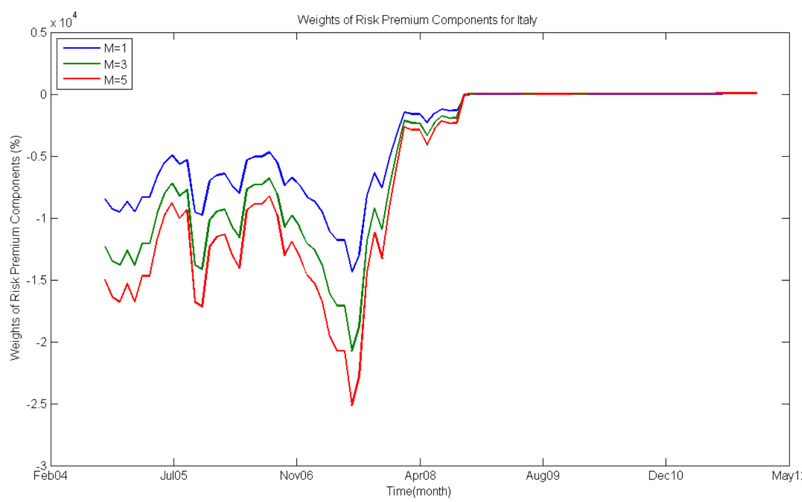

**Figure 6.1:** Decomposition of Five-year Sovereign CDS Contracts



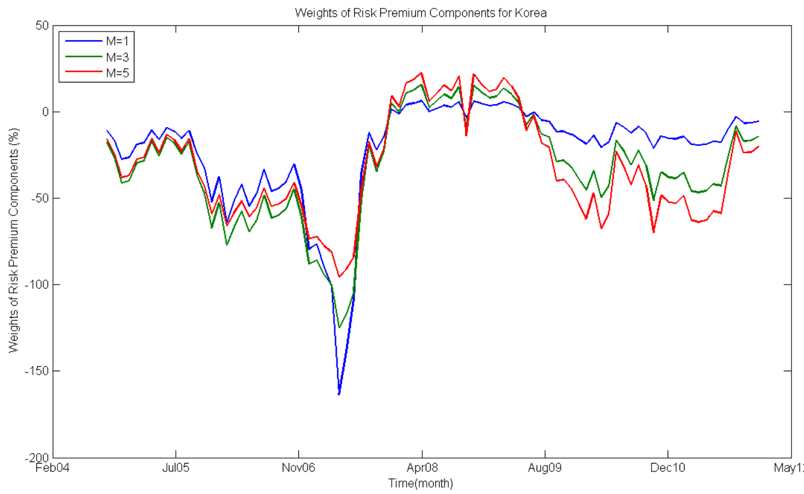
Weights of Risk Premium Components for China
M=1
M=3
M=5
Weights of Risk Premium Components (%)
Time(month)
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12

Weights of Risk Premium Components for Germany
x 10^5
M=1
M=3
M=5
Weights of Risk Premium Components (%)
Time(month)
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12

Weights of Risk Premium Components for Italy
x 10^4
M=1
M=3
M=5
Weights of Risk Premium Components (%)
Time(month)
Feb04
Jul05
Nov06
Apr08
Aug09
Dec10
May12



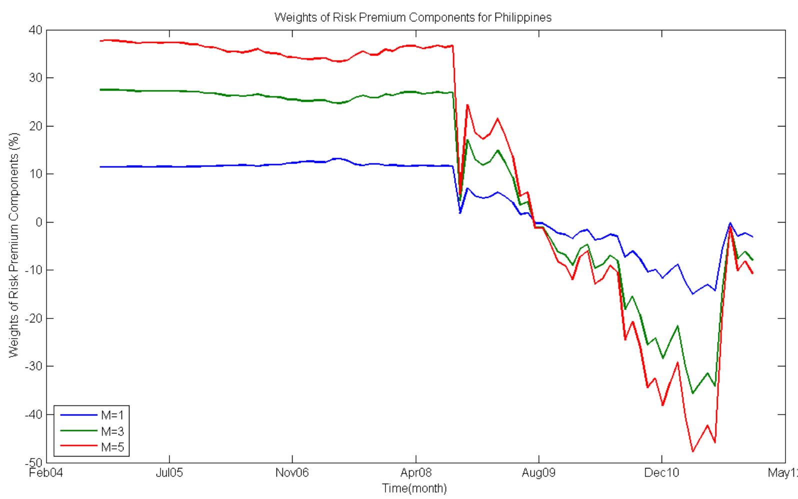




**Figure 6.2:** Weights of Risk Premium Components of Five-year Sovereign CDS

# Chapter 7

# Originality

As we mentioned earlier, this thesis follows a similar framework to the work of Longstaff et al. (2007), and the main originality of this thesis is the competent analysis of new data in terms of existing methods.

The work of Longstaff et al. (2007) focused on the sovereign CDS data of developing countries in Asia, Latin America, and Europe for the 2000 to 2010 sample period. While in this thesis, we put emphasis on the sovereign credit spreads of the emerging markets in Asia and the developed countries in Europe for the sample period from Sept 2004 to Aug 2012. This choice of data set helps us penetrate the following aspects: 1. The sovereign CDS structure comparison of Asian countries with European countries; and 2. The sovereign CDS structure comparison of the pre-crisis period with the post-crisis period.

Besides, this thesis is different from their work in some details of data analysis, such as the PC analysis for the full sample period and the two sub-sample periods, the methods used to get some explanatory variables, and the t-statistics based on autocorrelation and heteroskedasticity consistent covariance matrix estimates of Newey and West (1987) for the regression.

We do get some intriguing findings in terms of the two aspects. First, the regional factor has an important influence on sovereign credit risks. This is highlighted from the opposite signs of the loadings for the 2nd PC, the regression coefficients for covariates including foreign reserve, global stock market, and volatility risk premium, for Asian and Europen countries. Second, the structure of sovereign credit risk changes substantially after the 2008-2009 financial crisis, confirmed by the distinct PC analysis results for the two sub-sample periods.

Moreover, we have some different findings compared to those of Longstaff et al. (2007). Based on their regression analysis, they suggested that "the majority of sovereign credit risk can be linked to global factors", while our findings argue that both global factors and local factors play a vital role.

In addition to the data set difference, this thesis can also be distinguished from the work of Longstaff et al. (2007) by the different choices of pricing models. They assumed that the default rate $\lambda^{\mathbb{Q}}$ follows a log-normal process, while we chose the CIR model to simplify the estimation and calculation. Since we have noticed the structural differences of sovereign credit risks in the pre-crsis and post-crisis periods, we use MLE for model parameters for the two sub-sample periods.

# Chapter 8

# Conclusion

In this thesis, we study and analyze the nature of sovereign credit risks via the spread data of sovereign credit default swaps for selected countries in Asia and Europe, which includes both developed and developing countries with various credit ratings. Our results show that sovereign credit risks have different structures from local stock markets. And they tend to have stronger co-movements across countries after the 2008-2009 financial crisis than before.

Further regression analysis indicates that the stronger commonality of sovereign credit risks stem 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 regional sovereign spreads, such as a 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 sovereign CDS spreads, we use a standard model studied in Pan and Singleton (2008) and Longstaff et al. (2007). However, differently from these authors, we assume that the arrival rate of credit events follows a Cox-Ingersoll-Ross model. We find that there are differences between the performances of our credit risk pricing model if we use the maximum likelihood estimation method to estimate the underlying parameters for the full sample period. Considering the severe contrasts of sovereign credit risks before and after the financial crisis, we decide to divide the whole sample period into two sub-periods, and estimate the parameters for each sub-period separately. This greatly improves the performance of our model in terms of pricing accuracy.

Furthermore, we decompose the sovereign credit risk into distress risk premiums and credit-event components. The decomposition results show strong regional features as well. For Asian countries, credit-event components play a much important role in sovereign CDS markets than risk premiums. Our analyses also indicate that after the 2008-2009 financial crisis, the weights of risk premiums in total sovereign credit risk tend to decrease towards zero.

Finally, although sub-sample MLE estimation provides better and more acceptable results, our one-factor model still shows many drawbacks in pricing the sovereign credit spreads. Especially when financial crisis happens, the parameters that govern the intensity of credit risks change severely. For each situation, we could consider introducing jump diffusions to the square-root diffusion of $\lambda$, or introduce additional relevant factors. The thesis is also constrained by the availability of sovereign CDS data. A larger data set with various maturities for more sovereigns in a longer period would help us better understand the nature of sovereign credit risks.

# 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.

# Bibliography

Ahn, D.-H. and B. Gao (1999). A parametric nonlinear model of term structure dynamics. *Review of financial studies 12*(4), 721–762.

Ang, A. and G. Bekaert (2002). International asset allocation with regime shifts. *Review of Financial studies 15*(4), 1137–1187.

Ang, A. and F. Longstaff (2011). Systemic sovereign credit risk: Lessons from the us and europe. Technical report, National Bureau of Economic Research.

Aristovnik, A. and T. Čeč (2009). Compositional analysis of foreign currency reserves in the 1999-2007 period: The euro vs. the dollar as leading reserve currency.

Arshanapalli, B. and J. Doukas (1993). International stock market linkages: Evidence from the pre-and post-october 1987 period. *Journal of Banking & Finance 17*(1), 193–208.

Attinasi, M., C. Checherita, and C. Nickel (2009). What explains the surge in euro area sovereign spreads during the financial crisis of 2007-09?

Augustin, P. and R. Tédongap (2011). Common factors and commonality in sovereign cds spreads: A consumption-based explanation. Technical report, Working paper.

Baek, I., A. Bandopadhyaya, and C. Du (2005). Determinants of market-assessed sovereign risk: Economic fundamentals or market risk appetite? *Journal of International Money and Finance 24*(4), 533–548.

Baldacci, E., S. Gupta, and A. Mati (2008). Is it (still) mostly fiscal? determinants of sovereign spreads in emerging markets. *IMF Working Papers*, 1–23.

Berndt, A., R. Douglas, J. Duffie, M. Ferguson, and D. Schranz (2004). Measuring default risk premia from default swap rates and edfs.

Bluhm, C., L. Overbeck, and C. Wagner (2002). *An introduction to credit risk modeling*. Chapman & Hall/CRC.

Chow, G. (1994). *Understanding China's economy*. World Scientific Publishing Company Incorporated.

Cochrane, J. and M. Piazzesi (2002). Bond risk premia. Technical report, National Bureau of Economic Research.

Dahlquist, M. and H. Hasseltoft (2011). International bond risk premia. *Swiss Finance Institute Research Paper* (11-16).

Driessen, J. (2005). Is default event risk priced in corporate bonds? *Review of Financial Studies 18*(1), 165–195.

Eichengreen, B. and R. Hausmann (1999). Exchange rates and financial fragility. Technical report, National Bureau of Economic Research.

Exchange, C. (2009). The cboe volatility index–vix. *White Paper*.

Fama, E. and K. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics 33*(1), 3–56.

Fitz-Gerald, K. (2011, February). Global bond market outlook: Three ways to dodge the looming bear market in u.s. bonds.

Floros, C. (2009). Modelling volatility using high, low, open and closing prices: evidence from four s&p indices. *International Research Journal of Finance and Economics 28*, 198–206.

Fukuda, S.-i. and Y. Kon (2008). Macroeconomic impacts of foreign exchange reserve accumulation: A theory and some international evidence.

Garman, M. and M. Klass (1980). On the estimation of security price volatilities from historical data. *Journal of business*, 67–78.

Goetzmann, W., L. Li, and K. Rouwenhorst (2001). Long-term global market correlations. Technical report, National Bureau of Economic Research.

Grossman, H. and J. Van Huyck (1989). Sovereign debt as a contingent claim: Excusable default, repudiation, and reputation.

Hilscher, J. and Y. Nosbusch (2010). Determinants of sovereign risk: Macroeconomic fundamentals and the pricing of sovereign debt*. *Review of Finance 14*(2), 235–262.

(IMF), I. M. F. (2012). *World Economic Outlook: Growth Resuming, Dangers Remain.* International Monetary Fund.

Jolliffe, I. (2005). *Principal component analysis.* Wiley Online Library.

Longstaff, F., J. Pan, L. Pedersen, and K. Singleton (2007, April). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics 3*(2), 75–103.

Longstaff, F. A., S. Mithal, and E. Neis (2005). Corporate yield spreads: Default risk or liquidity? new evidence from the credit default swap market. *The Journal of Finance 60*(5), 2213–2253.

Mankiw, N. (2011). *Principles of microeconomics.* South-Western Pub.

Mauro, P., N. Sussman, and Y. Yafeh (2002). Emerging market spreads: then versus now. *The Quarterly Journal of Economics 117*(2), 695–733.

McGuire, P. and M. Schrijvers (2003). Common factors in emerging market spreads. *BIS Quarterly Review, December*.

Merton, R. and P. Samuelson (1990). Continuous-time finance.

Mohanty, M. and P. Turner (2006). Foreign exchange reserve accumulation in emerging markets: what are the domestic implications? *BIS Quarterly Review, September*.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica: Journal of the Econometric Society*, 703–708.

Palley, T. (2004). The economics of exchange rates and the dollarization debate.

Pan, J. and K. Singleton (2008). Default and recovery implicit in the term structure of sovereign cds spreads. *The Journal of Finance 63*(5), 2345–2384.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of Business*, 61–65.

Pineau, G., E. Dorrucci, F. Comelli, and A. Lagerblom (2006). The accumulation of foreign reserves. *ECB Occasional Paper* (43).

Remolona, E., M. Scatigna, and E. Wu (2007). The dynamic pricing of sovereign risk in emerging markets: fundamentals and risk aversion. In *20th Australasian Finance & Banking Conference.*

Rogers, L. and S. Satchell (1991). Estimating variance from high, low and closing prices. *The Annals of Applied Probability*, 504–512.

Schönbucher, P. (2003). *Credit derivatives pricing models: models, pricing and implementation*. Wiley.

Sugihara, Y. (2010). Global contagion of volatilities and volatility risk premiums. Technical report, Working paper.

Unit, E. I. and G. Britain (2011). *State of the Union: Can the Euro Zone Survive Its Debt Crisis?* Economist Intelligence Unit.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society*, 817–838.

Yang, D. and Q. Zhang (2000). Drift-independent volatility estimation based on high, low, open, and close prices*. *The Journal of Business 73*(3), 477–492.

Zhang, F. X. (2003). What did the credit market expect of argentina default? evidence from default swap data. In *AFA 2004 San Diego Meetings*.

Zhu, C. and D. Lague (2012, October 18). In china, a power struggle of a different order. The International Herald Tribune.