Essays On The Credit Default Swap Market Of Sovereign Bonds

by

Nan Li

A dissertation submitted to the Graduate Faculty in Economics
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy, The City University of New York

2005

UMI Number: 3187419

ProQuest Information and Learning Company
300 North Zeeb Road
P.O. Box 1346
Ann Arbor, MI 48106-1346

This manuscript has been read and accepted for the Graduate Faculty in Economics in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

April 21, 2005	Salih N. Neftci
Date	Chair of Examining Committee
April 21, 2005	Thom B. Thurston
Date	Executive Officer

Professor Salih N. Neftci

Professor Turan G. Bali

Professor Michael Grossman

Supervisory Committee

THE CITY UNIVERSITY OF NEW YORK

Abstract

Essays On The Credit Default Swap Market Of Sovereign Bonds

by

Nan Li

Adviser: Professor Salih N. Neftci

Credit Default Swap(CDS) is the building stone of hedging strategies for credit exposures, and the basis of more advanced credit derivative products. The valuation of the contractual annum payment of a CDS product has also established a new pricing system of credit default risk, in relation to the traditional yield spreads implied from bond prices.

The focus of this dissertation is the CDS market of sovereign bonds, especially those issued by developing or newly developed countries. There are two essays included: the first essay is a steady state analysis on the implied benchmark rate in sovereign CDS market, the second essay is a study on the dynamic relationship of CDS rates and yield spreads. In the first essay, the implied benchmark is computed and compared with observable benchmarks such as US Treasury yield and LIBOR rate. This reveals that the implied benchmark rate is more related to US Treasury yield than the market favorite–LIBOR rate. It is also observed that there is a pricing gap between the CDS rates of sovereigns at investment grade and those at speculative grades.

The second essay examines the relationship of CDS rates and yield spreads both in long run and in short run. It is found that their equilibrium can only be reached in a long run; price disparity exists in a short run; credit price discovery is dominated in bond market other than CDS market. Among the determinants of the price disparity, liquidity variable contributes to a half of the overall explanatory power. Its impacts on the value of price disparity and its volatility are scrutinized. All the findings aim at application in academic research or trading strategies.

Acknowledgements

I would like to express my deepest gratitude to Father God for His salvation and immeasurable Love, and for granting me the precious opportunity to be a CUNY graduate. I would also like to thank my advisor, Professor Salih Neftci, who has been an excellent teacher and supervisor to me, and my Professors, Thom Thurston and Michael Grossman, for their tremendous help and support with my studies. Special thanks go to my family: my mother, Bian Li, my father, Guogu Li, and my lovely younger sister, Ting Li, for their endless love and encouragement. There is a great couple that I am always grateful to: Feili Ye and Miao Wang, who love me, protect me and help me without limit. I am also grateful to my pastor, Mudao Xiao, and his wife, who are like a second father and mother to me. Lastly, I wish to thank my close classmates and my Church brothers and sisters. It is a great honor and privilege to know them and have them in my life.

My dissertation, which leads to the completion of the Ph.D program in economics, does not belong to myself. It belongs to the economics department of GC, CUNY and my family.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

The development of credit default swap(CDS) market is to extract credit risk from other risks, and trade on it more efficiently. A CDS rate represents the default risk premium expected by market. Besides, the yield spread calculated by bond yield over default-free rate, is an traditional measure of default risk. As CDS market becomes more developed, the convergence of these two default risk measures and the efficiency of CDS market are being widely questioned and examined by people from academia and industry.

The purpose of this study is to explore the features of the newly developed sovereign CDS market from various aspects. Chapter 2 is a summary on CDS market, chapter 3 shows findings in previous research, chapter 4 analyzes the implied benchmark rate in sovereign CDS market compared with corporate CDS market, chapter 5 studies the relationship of sovereign CDS rates and corresponding yield spreads.

1.1 Credit Default Swap(CDS) Market

1.1.1 Credit Default Swap(CDS) Products

A Credit Default Swap(CDS) product is a contract signed between two parties, subject to the liability owed by a third party. The buyer of a CDS contract pays a predetermined fixed amount of annual fee, called as 'CDS rate' or 'CDS spread', to protect his investment on the liability against its default. The liability which is invested by the CDS buyer and issued by the third party, is called 'underlying asset'; where the third party, the issuer of the liability, is called 'reference entity'. Since the CDS market is an over-the-counter market, both the size of the underlying asset and the value of CDS rate in a CDS product are negotiable.

There is more than one type of CDS product. A Single-name credit default swap is written on single reference entity. It is the most fundamental product in the market. A multi-name credit default swap contract such as basket credit default swap or credit default swap index, is written on multiple reference entities. CDS products can also be divided into two sectors by the types of reference entities: the corporate(including banks) CDS and sovereign CDS. The focus in this study is single-name CDS products in sovereign sector. Although most sovereigns issue both domestic and euro bonds, only euro bonds are discussed here.

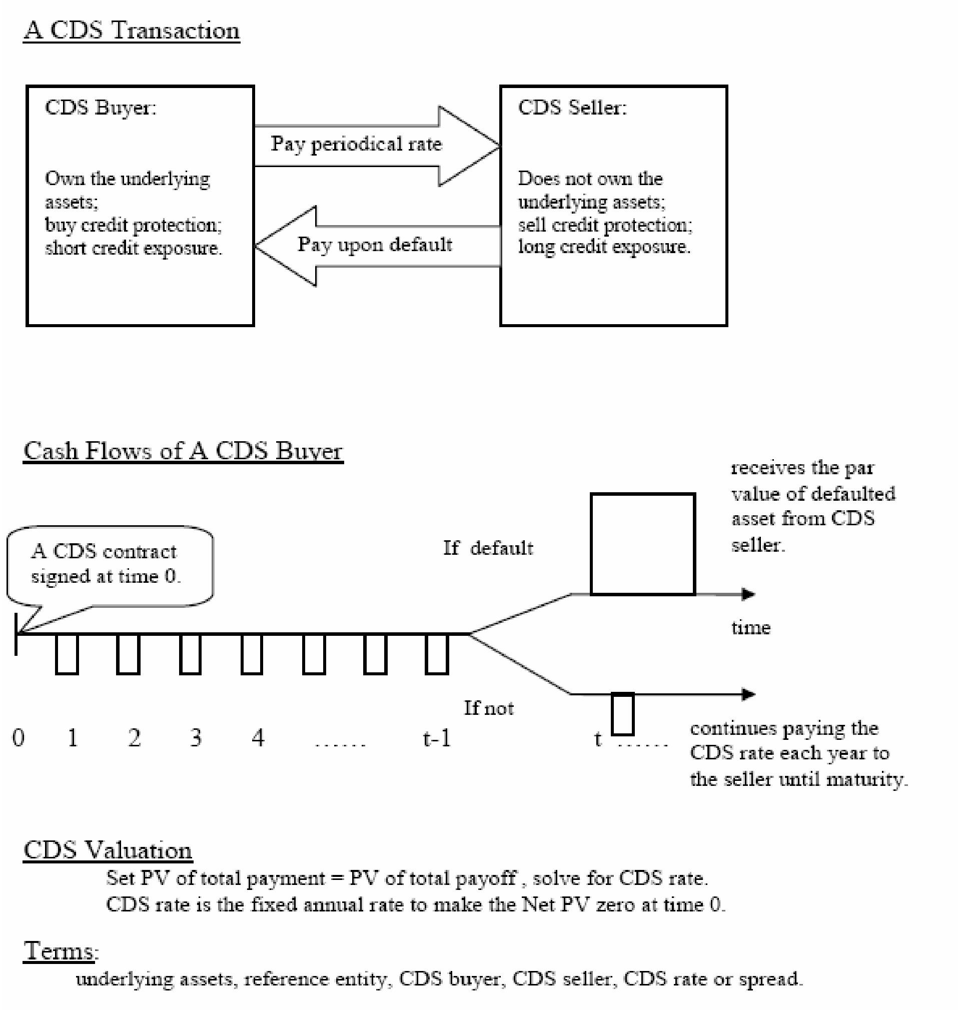

Figure 1.1: A CDS contract

1.1.2 Market Growth

Driven by the needs from both outside and inside of credit market, the Credit Default Swap(CDS) market has become the most developed derivative market in recent decades in the financial world. According to the report by the British Bankers' Association, credit derivative market grows from a USD 40 billion outstanding notional value in 1996 to an estimated USD 8.2 trillion at the end of 2006. Both American and European markets are active in CDS trading.

CDS products, first created to insure the outstanding credit risk, have become a hedging instrument and the underlying asset of more advanced credit derivative products such as Collateralized Debt Obligation(CDO). The explosive growth is more an effect of inter-dealer trading than risk transference motivation. A recent market report argues that a new investor's participation in a single tranche CDO could spur instantaneous leveraged demand for the underlying CDS products. Some dealers now offer structured credit products with CDS delta exchange to attract investors. The reference entities of CDS products used in this capacity are usually highly rated borrowers. Meanwhile, CDS products used for insuring purpose are mostly under the entities in speculative rating grade. Largely due to the introduction of standardized iTraxx tranches in September, 2004, rapidly growing CDS market accompanies an increase in market liquidity. The 10-year CDS now becomes the second most liquid product after the 5-year CDS.

1.1.3 Market Participants

The following table presents survey data collected by Risk magazine in 2002. The end-user statistics shows the structure of market participants in year 2002. On the buy side of the market, hedge funds, asset managers, insurance and corporations constitute 27% of total, with hedge funds and asset managers growing at a faster pace. The number of active market participants has increased from 10 market participants with CDS prices on 100 reference names in 2000, to more than 30 banks and brokers as market makers on over 300 names in 2002.

Table 1.1: Selected Credit Derivative Market Statistics in 2002

CDS by Origin of Underlying Credit	%	End-User Breakdown	%
America	44	Banks	47
Europe	40	Reinsurance	14
Asia	12	Insurance	9
Emerging Markets	5	Hedge Funds	8
		Banks(securitization)	8
		Asset Managers	6
		SPV/SIVs	4
		Corporations	4

(Source: 2002 Risk Magazine Credit Derivative Dealer Survey)

Recent market reports indicate that the structure of market participants has been shifting dramatically. The changes mostly happen in the structure of CDS sellers. Hedge funds, once traded actively as buyers, have shifted to become major CDS sellers. Their trades comprising of 20%-30% of market volume, are still rapidly growing. Many large banks and broker dealers have also moved from being net buyers to being net sellers.

1.1.4 Sovereign CDS Market

Sovereign CDS is more liquid than other credit derivative products in emerging markets. According to the research by Packer and Suthiphongchai(2003), the activity of sovereign CDS experienced a decline during 2002. The decline resulted from Argentina's default in Dec. 2001 and a drop in transactions for Asian names such as China, Korea and Thailand. The CDS trades in Asian names has stabilized in 2003, while growth in Latin American names such as Brazil and Mexico continued.

1.2 The Difference Between Sovereign And Corporate CDS Markets

For sovereign CDS products, the number of quotes and the borrower names are much smaller than corporate CDS products, but their average volume of quotes per name is greater than corporate CDS. The degree of concentration in activity is very high in sovereign names. According to Packer and Suthiphongchai (2002), the five leading names in sovereign CDS market are Brazil, Mexico, Japan, the Philippines and South Africa. They constitute more than 40% of listed quotes. In contrast, the top five names in corporate CDS take only 7.7% of the total corporate quotes on CreditTrade.

The overall credit quality of sovereign CDS names tends to be lower than the corporate names. 40% of sovereign obligation is at speculative grade

(BB and below), with only 10%-15% rated at AAA or AA. At ratings A and above,sovereign CDS quotes are generally lower than those of corporations; at ratings below BB, they are quoted higher than corporate names. For instance in 2003, the average quote of AAA-rated sovereigns CDS was approximately 30 basis points below that of corporate; for AA- or A-rated CDS, the average difference was approximately 40 and 50 basis points, respectively.[1].

[1]For a complete review on sovereign CDS market, see International Banking and Financial Market Developments, BIS Quarterly Review, December 2003 page 87

Chapter 2

Previous Research

2.1 Determinants Of Yield Spreads

Credit risk has been extensively discussed since late 1900. Previous research focus on the dynamic pricing mechanism of Credit risk premium. There are two types of models extensively used: structural models by Black and Scholes(1973) and Merton(1974); reduced form models by Litterman and Iben(1991), Jarrow and Turnbull(1995).

In the family of structural model, credit risk is quantified as deterioration of a firm's asset value: once the asset value falls below a default boundary, default occurs and the firm is dismissed. Thus, factors which affect the firm's underlying assets should also be the determinants of the yield spreads of the bonds issued by the firm. These factors can be divided into three categories: macro-level, industrial, and firm-level. Among them, the most significant proxies used in the past are yield curve, stock price, stock price volatility and financial leverage. In the sovereign case, macro indices such as exchange rate and GDP level in the country are deemed as firm-level factors instead of firm leverage. Although these factors are found to be statistically significant in previous literature, their total explanatory power on the variation of yield spreads is quite small. Collin-Dufresne, Goldstein and Martin(2000) argue that a large part of the dynamics of corporate yield spreads cannot be explained by the common variables. Gruber, Agrawal and Mann(2001) find that corporate credit spreads are better explained by tax effect and a risk premium than by expected default probability. These arguments raise questions regarding the validity of structural model.

Reduced form model(also known as intensity-based model) then, is introduced into credit research. This model treats the default time as a random stopping time with a stochastic arrival intensity. Default density measures the instantaneous default risk in a risk neutral valuation of bond price. Previous research find evidences of taxation, default and liquidity components in yield spreads. Gruber, Agrawal, and Mann (2001) find that the expected default risk only explains about 25% of the observed credit spreads. Longstaff, Mithal and Neis (2004) find that liquidity factors are both the systematic and idiosyncratic components of bond spreads.

In seeking a full structure of yield spreads, scholars recently pool components experimentally in structural and reduced form models together, and test their total explanatory ability to the variations of yield spreads. For example, Driessen (2003) decomposed yield spreads into taxation, liquidity risk, common factor risk, default event risk, default-free factor risk and firm-specific factor risk components. He found the explanation power improved obviously.

In analyzing yield spreads of sovereign bonds, Edwards(1984) and Ming(1998) used trade balance, GDP growth rate, exchange rate, domestic inflation rate and terms of trade as country-level factors; used debt-to-GDP ratio, debt-service-ratio, net foreign assets and international-reserves-to-GDP ratio as default variables within structural models. Claessens and Pennachi (1996), and Duffie, Pedersen, and Singleton (2000) used default density, credit risk correlation and interest rate term structure in reduced form models.

2.1.1 Arguments On Liquidity Components

Among all these components, liquidity risk is said to be the secondary most important factor in yield spreads besides default risk. However relevant studies provide different sets of evidence and results in different viewpoints. Schultz (2001) estimates that round-trip(buy and sell) trading cost in the US corporate bond market is about 27 basis points and uses it as a measure of liquidity premium in bond yields. Fleming (2001) uses the difference between on-the-run and off-the-run treasury yields as a proxy of liquidity premium, ranging from 10 to 25 basis points. [1] Although liquidity premium is not negligible, these studies find that it only accounts for a small proportion of yield spreads and should not be a major or important component. A recent argument gives a new explanation on this contradiction. It states that the proxies being used for liquidity premium are far from sufficient, because they have only included the expected loss from historical data, not the premium

[1] The most recently issued Treasuries are said to be on-the-run. There is a liquid secondary market for on-the-run Treasuries. Other Treasuries are said to be off-the-run, and they have less of a secondary market. Because they lack liquidity, off-the-run Treasuries are routinely traded at spreads over comparable on-the-run Treasuries.

against the unexpected loss in liquidation. When both parts are measured, liquidity risk becomes the next important risk component after default risk in bond spreads.

2.2 Comparing CDS Rates With Yield Spreads

Available literatures on the relationship of CDS rates and yield spreads which is mostly interested by market practitioners, is more scarce. Amato and Remolona (2003) observe that yield spreads of corporate bonds tend to be many times wider than what would be implied by expected default losses alone. They call this phenomenon "credit spread puzzle" and suspect that an undiversified credit risk embedded in yield spreads. This argument initiates studies on pricing equilibriums of credit risk embedded in different financial products. However, conclusions gleaned from these studies are not in consensus.

Houweling and Vorst (2001)and Hull et al (2003) both argue that when USD swap rate is used as risk-free rates, the price discrepancies between bond spread and CDS rates are quite small both in short run and long run. However, Chan-Lau and Kim (2004) find no equilibrium price relationship between sovereign CDS and sovereign bond markets, although prices converge in long term. Zhu(2004) finds the price discrepancy between CDS rates and yield spreads very substantial in short run. Blanco et al(2004) analysis dynamic relationship between investment-grade bonds and credit default swaps, and conclude that CDS rates is the upper bound and yield spreads is the lower bound of credit risk premium.

Chapter 3

Implied Benchmark In CDS Market

Researchers and market participants both prefer LIBOR to US Treasury rate as the measure of implied risk-free rate(also called 'benchmark rate') in CDS market, since LIBOR rate is less volatile and more reasonable. However, in this study, I find that US Treasury rate is more eligible to be the proxy of the implied benchmark than LIBOR rate in sovereign CDS market.

3.1 Methodology

In this section, I adopt Hull et. al(2004)'s regression models to study the closeness of US Treasury or LIBOR to CDS benchmark. Rating shocks are imposed later to the regressions to reexamine the findings. Analytical study on market behavior follows to determine the reasons behind the result.

3.1.1 A Contemporary Arbitrage Relationship

A CDS contract is usually bought by investors in the corresponding bond market, to earn an insured risk free return by transferring their default risk to CDS sellers. This risk free return is the difference of bond yield over CDS rate, called 'implied benchmark rate'.

Calculation Formula: $r = y - s$

Here, y is n-year par yield, s is n-year CDS rate, and r is the n-year implied benchmark rate. If CDS and bond markets are well cointegrated,and the CDS rate is correctly priced, r should equal other benchmark rates observed in bond market, such as US Treasury yield or LIBOR rate. A set of arbitrage relationships are shown as follows.

Arbitrage relationship: $r = r_T$; $r = r_S$.

Where,r_T denotes US Treasury yields, r_S denotes LIBOR rates. When the first arbitrage holds, the CDS rate will also be equal to the corresponding yield spread. The equilibrium of implied benchmark rate and US Treasury yield is the same equilibrium of CDS rates and yield spreads.

3.1.2 Regression Models In Hull et al(2004)

In practice, the equilibrium is usually affected by the following reasons:

1. The cheap-to-deliver bond option in CDS contract
2. The counterpart default risk in CDS market
3. The Repo cost in bond yield

4. Liquidity difference of CDS and bond markets

5. Regulation (like taxation) difference in two markets

Besides, as discussed by Hull et al(2004), CDS contracts give the holders the right to sell the par bonds for their face value plus accrued interest, so CDS rates should be adjusted by the accrued interest due before default.[1] $\frac{y}{4}$ is used to measure the accrued interest. The calculation of implied benchmark therefore is also adjusted.[2]

Adjusted Formula:

$$r = y - s(1 + \frac{y}{4}) \tag{3.1}$$

The equilibrium relationships are tested by two similar regressions.

Regression Models:

$$r = a + b_1 r_T + \epsilon \tag{3.2}$$

$$r = a + b_2 r_S + \epsilon. \tag{3.3}$$

By applying regression models (equation (3.2) and (3.3)) from Hull et al's, I firstly examine the arbitrage relationship by the joint hypothesis $H_0 : a = 0$ and $b = 1$; then, two separate hypotheses $H_0 : a = 0$ and $H_0 : b = 1$. To compare with Hull et al's results, student t tests are listed.[3]

[1]See Hull et al(2004) for detailed description.

[2]These linear regressions are valid since the explanatory variable r_T or r_S is not systematic correlated with ϵ: the disturbances in CDS market.

[3]F test on the joint hypothesis is different from t tests on each part of the joint hypothesis. T tests are necessary when the joint hypothesis is rejected. Since both Hull et

3.1.3 The Impact Of Rating Events On The Relationship

Rating events are updated public information on credit risk changes. They directly affect credit prices in both bond and CDS markets. Previous research on the relationship of CDS rates and ratings finds that the negative outlook of a borrower will push up its CDS rates; but formal rating change will not bring big shocks to CDS market. Similar findings are made in previous research on the relationship between bond prices and ratings.

When benchmark equilibrium is loosely held, or the correlation between the benchmark rates is statistically stable, new incoming information should have the same impact on CDS rates and bond yields, and should not affect the benchmark equilibrium. To test this argument, a measure of rating events– q is added into equation (3.2) and (3.3).

Rating events include rating changes and outlook changes. Value of q at time t is generated by

$$q_t = \frac{m_t}{n_t}.$$

Where, m_t is the total number of rating events until time t, n_t is the total number of the total observations until time t. q is not the cumulative frequency or probability of rating events, since n_t is changing over time. [4] Thus, two extended regression models are also estimated:

$$r = a + b_1 r_T + cq + \epsilon \tag{3.4}$$

al's research and my results reject the strict arbitrage relationship, t tests are applied

[4]The cumulative probability is calculated by the total number of observations which is constant over N.

$$r = a + b_2 r_S + cq + \epsilon. \tag{3.5}$$

3.2 Data Analysis

In this dissertation, I use daily data of sovereign Euro-bond yield spreads, CDS rates, and US Treasury yields from 04/01/1999 until 5/22/2002, provided by an anonymous broker. From among them, I choose 5 years as the constant time to maturity, since 5-yr CDS is the most liquid. 5-year daily LIBOR rates are from the online database of the Federal Reserve. Information on rating events are extracted from S&P's Rating History. There are a total of 46 Euro-bonds under 20 sovereign entities, mostly in emerging markets.

To get 5-year bond yields of each sovereign entity, I use linear interpolation of reference yields under the same sovereign name and get 2401 yield spreads under 8 sovereigns. 12 sovereigns are dropped due to the lack of reference bonds, or unmatched time to maturity. [5]

According to S&P's rating history (see Table 11), during 04/01/1999 to 05/22/2002, there are 48 rating events of the 8 sovereigns, including rating changes and outlook changes. Their ratings at 05/22/2002 are:

Investment Grades			Speculative Grades				
Korea	South Africa	Mexico	Egypt	Russia	Brazil	Venezuela	Argentina
A-	BBB	BBB-	BB+	BB	BB-	B	D

[5] The interpolation requires at least one bond with a time to maturity(T) less than 5 yrs, and one bond with a T longer than 5 yrs and shorter than 10 yrs.The selected sovereigns usually have 2 or 3 reference bonds, the linear spine interpolation approach is adopted.

The Euro-bonds are in US dollars with fixed semi-annual coupons. They are assumed to have identical properties, so that their yield spreads only embed sovereign-level default premiums, no bond-specific default premiums need to be considered.

3.3 Regression Results

3.3.1 Overall Arbitrage Relationship

Hull et al(2004)'s t tests show $a = 0$ is accepted but $b = 1$ is rejected; the arbitrage relationship is not strictly held. However, the values of r and r_S are found very close, in practice, r–the implied benchmark can always be measured by inflating r_S–LIBOR rate with 10bps.[6]

Except defaulted Argentina, 7 sovereigns from rating A to B are pooled together and estimated. Both F and t tests reject the equilibrium hypotheses at 95% confidence level. r_T explains 31.95% of total variation in implied benchmark r in the regression of equation (3.2); r_S explains 28.57% of total variation in r in the regression of equation (3.3). The difference between the two regressions is found significant through $F_{1935,1935}$ test. By comparing the two benchmark's explanatory powers, US Treasury yield is a better regressor and proxy to the implied benchmark, than LIBOR rate.

[6] 10bps gets from the estimate of $r - r_S$ for Aaa and Aa borrowers in Hull et al(2004). The estimates for other rating classes are not used for the measure in order to get rid of the counterpart default risk in a CDS contract. See Hull et al(2004) for details.

Table 3.1: Pool Regressions on US Treasury Yield(r_T)

	Hull's Case	Sovereign Case		
		Pool	Investment Grade	speculative grade
a	0.12	-1.05359	0.33422	-2.79665
SE of a	0.07	0.18143	0.12573	0.21509
b_1	1.1	1.19831	1.01946	1.49835
SE of b_1	0.014	0.03973	0.02839	0.04628
SE of Residual	0.25	0.85261	0.27374	0.86382
Adjusted R^2	0.941	0.3195	0.6402	0.4637
No.	370	1937	725	1212

3.3.2 Loose Equilibrium At Investment Grade Rating

Due to the variety of the ratings across samples, the 7 sovereign samples are separated into two groups : 3 at investment grade and 4 at speculative grade. Group regressions of both equations are carried out, and estimates are reported in Table 1 and Table 2. Hull et al's results are also listed as a reference. Chow test indicates the significance of the structural difference over the two groups. The formula of Chow test is written as:

$$F = \frac{(RSS_1 - RSS_2 - RSS_U R)/K}{(RSS_1 + RSS_2)/(N - 2K)}.$$

The computed F values are

$$r_T : F_{chow} = 453.50; r_S : F_{chow} = 390.77,$$

they are both very significant. The goodness of fit and the standard errors have greatly improved in group regressions. It also indicates the existence of pricing gap between investment and speculation rating grades.

Among these results, the regression on US Treasury yield in investment

Table 3.2: Pool Regressions on LIBOR Rate(r_S)

	Hull's Case	Sovereign Case		
		Pool	Investment Grade	Speculative Grade
a	0.09	-0.37150	0.79152	-1.87362
SE of a	0.059	0.17207	0.13129	0.20628
b_2	0.972	0.90367	0.79075	1.11860
SE of b_2	0.01	0.03245	0.02559	0.03819
SE of Residual	0.203	0.87352	0.30086	0.90268
Adjusted R^2	0.961	0.2857	0.5686	0.4144
No.	370	1937	725	1212

grade group is the most significant and the equilibrium exists. It has better fit, where $a = 0$ is accepted at 0.5% significant level, and $b = 1$ is accepted at even higher significant level. But the equilibrium is not held for the regression on LIBOR in investment grade group and all regressions in speculation group. Compared with Hull et al's results, the estimate of intercept a is much greater in absolute value and the goodness of fit is lower. These may imply the existence of other latent fixed and/or random variables. Besides, the closeness of US Treasury yield to the implied benchmark becomes more obvious in group regressions.

3.3.3 Rating Events Affect The Relationship At Speculative Grade Rating

By the time series of rating events q is added to the original equation, extended models (3.4)and (3.5) are also regressed. The impacts of rating changes and outlook changes are estimated separately to compare the difference.

There are 6 rating changes and 8 outlook changes in the pool regressions of

Table 3.3: Regressions for Speculative Group

	US Treasury yield r_T		
	——	Rating changes	Outlook changes
a	-2.79665	-2.18104	-2.08156
SE of a	0.21509	0.15145	0.22554
b	1.49835	1.35707	1.38401
SE of b	0.04628	0.03119	0.04698
q	——	30.17247	-73.97128
SE of q	——	3.34295	8.74955
SE of Residual	0.86382	0.52784	0.83971
Adjusted R^2	0.4637	0.6706	0.4932
	LIBOR rate r_S		
	——	Rating changes	Outlook changes
a	-1.87362	-1.32624	-1.16526
SE of a	0.20628	0.15160	0.21857
b	1.11860	1.01949	1.02210
SE of b	0.03819	0.02693	0.03900
q	——	21.60688	-75.53949
SE of q	——	3.62235	9.19735
SE of Residual	0.90268	0.57701	0.87887
Adjusted R^2	0.4144	0.6064	0.4449

7 sovereigns. Besides, Argentina has 7 rating changes and 4 outlook changes before its default. Although the estimates of partial coefficient of q for each group are both significant, the regressions in speculative grade group are more improved than the original ones, and the impact of rating change is more significant than outlook change; while, the regressions at investment grade group have no big change. This implies that the CDS rates with lower rated reference entities are more sensitive to credit events. Historical statistics from previous studies also show that default probability changes are larger for the rating migrations within speculative grade. The estimations for speculative grade group are summarized at Table 3.3. The regression on Argentina is presented at Table 8 in appendix. Due to the limitation of rating events, I

did not differentiate the changing directions of these events.

3.4 An Analytical Study

3.4.1 Why Implied Benchmark Closer To US Treasury?

Hull et al argue that LIBOR and US Treasury are the efficient upper and lower boundaries of the implied benchmark, and the value of r is closer to LIBOR. According to this study, however, the argument is only true for sovereign borrowers at investment grade. For borrowers at speculative grade, the implied benchmark drops below US Treasury yield. US Treasury is more efficient than LIBOR to be the upper bound. These differences are illustrated at following inequalities and Table 3.4.

Hull et al(2004)'s Case:

$$r_T \leq r \leq r_S; \frac{r - r_T}{r_S - r_T} = 0.904 \tag{3.6}$$

Sovereign Case:

Investment Grade

$$r_T \leq r \leq r_S; \frac{r - r_T}{r_S - r_T} = 0.60154; \tag{3.7}$$

speculative grade

$$r \leq r_T \leq r_S; \frac{r - r_T}{r_S - r_T} = -0.66847. \tag{3.8}$$

Table 3.4: Mean of benchmarks

Benchmarks	The Mean Procedure		
	Pool	Investment Grade	speculative grade
r	4.3876	4.8342	4.12042
r_T	4.5407	4.4141	4.61646
r_S	5.2664	5.1125	5.35850

To find the hidden reasons of these findings, I summarize the descriptive statistics of the rating-specific implied benchmark at Table 3.5. Hull et al(2004) observe the implied rate rises when rating is declining. They argue that it is partially caused by the counterpart's default risk in a CDS contract, and are open to the possibility of other factors. While, in sovereign case, I find an opposite phenomenon– the implied rate is declining with rating. This means that the higher risky CDS contracts you buy, the lower the borrowing cost and the better of your capital gain. Since the explanation in Hull et al(2004) can not apply, the reason might come from the relative values of CDS rate and yield spreads.

3.4.2 Why Implied Benchmark Less Than US Treasury?

Given the formula of the implied benchmark, its relative position to US Treasury is actually driven by the relationship of yield spreads and CDS rates.[7]. When yield spreads exceed CDS rates, default risk premia in CDS market are cheaper, and the implied benchmark will become greater than US Treasury; vice versa. When a borrower's credit quality declines, both yield

[7]Yield spreads is defined by the yield of defaultable bond over US Treasury yield, represents the default risk premium in bond market

Table 3.5: Comparison Table

	Rating	$r - r_T$		$r - r_S$		No.
		Mean	S.E.	Mean	S.E.	
Sovereign Bond Case						
Korea	A-	0.621364	0.0125609	-0.08167	0.0104588	247
South Africa	BBB	0.458158	0.02095	-0.1797	0.02013	144
Mexico	BBB-	0.254863	0.0122359	-0.46618	0.0174240	334
Investment Grade	———	0.42011	0.0102	-0.27828	0.01167	725
Egypt	BB+	0.16208	0.05497	-0.4623	0.04844	104
Russia	BB	-0.05197	0.0204105	-0.8058	0.0222210	374
Brazil	BB-	-0.70571	0.0221534	-1.49305	0.0200528	452
Venezuela	B	-0.99163	0.0863562	-0.68884	0.0869170	282
Argentina	D	-11.7831	0.9739806	-12.5745	0.9709332	464
speculative grade	———	-0.49604	0.02596	-1.23809	0.02602	1212
Pool	———	-0.15313	0.01949	-0.87884	0.01989	1937
John Hull's case						
	AAA/Aa	0.5130	0.0197	-0.0955	0.0131	
	A	0.6433	0.0182	-0.0583	0.0159	
	BBB	0.8493	0.0363	-0.0221	0.0279	
	Pool	0.6287	0.0138	-0.0651	0.0106	

spreads and CDS rates will rise. If they both appreciate with the same pace and magnitude, the relative position of implied benchmark to US Treasury would not be affected. When this is not true, it means that CDS rates rise faster at credit quality decaying. Since the implied benchmark for borrowers at speculative grade is lower than US Treasury, this implies that the CDS rates in this category are much more expensive than the corresponding yield spreads.

3.4.3 Why CDS Higher Than Yield Spreads?

Graphic Relation

The comparison of yield spreads and CDS rates is illustrated by Figure 2-5. Graphs in Figure 2 are sovereigns at investment grade: Korea, South Africa and Mexico. Their CDS rates are consistently lower than the corresponding yield spreads. A gap between CDS rates and yield spreads is clearly observed at the beginning of each sample, but diminishes at the end of the sample. For example in the Mexico sample, there is only one upgrade rating event on Feb. 2002, but the gap started converging 10 months earlier and diminished 4 months earlier than the event date. So, rating change is not the reason to the price convergence in this case.

Figure 3-5 list sovereigns at speculative grade. CDS rates of Egypt are very illiquid, the price gap does not shrink. The values of CDS rates exceeds those of yield spreads since March 2002, two months before its rating downgrade, which may imply a market preadjustment. In Russia and Venezuela, CDS rates are below yield spreads at starting date, and beyond them from the middle of year 2001. Compared with investment grade, price differences at speculative grade are much smaller, and CDS curves are more smooth, showing improvement of liquidity. In Brazil, CDS rates are very liquid and consistently higher than yield spreads. But the price difference converges from time to time, showing more integration of the two markets. Argentina has exceptional data after its default in 2001, its CDS rate firstly jumps to 14000bps, then drops to 10000bps level. The jumps in CDS rates are ahead of the continuous changes in yield spreads during this after-default period, behaving as a leading indicator.

Regressive Relation

Using sovereign-specific linear regressions, the overall correlation of CDS rates and yield spreads is outlined at Table 9 and 10. These regressions are better fit and more significant than previous ones. Results on Egypt and South Africa are insignificant due to illiquid CDS.

The estimates of intercept are insignificantly different from zero, and coefficient estimates of CDS rates vary from 0.8 to 1.4, except for Egypt and South Africa. Estimates for sovereigns at investment grade are greater than 1, showing the yield spreads is statistically higher than CDS rates; estimates at speculative grade are less than 1.

An Explanation By Market Demand And Supply

Blanco et al(2004) discuss that CDS rate is the upper bound and yield spread is the lower bound of credit risk premium, implying CDS rate should be analytically higher than yield spread. Where, Hull et al(2004)'s study suggests an opposite measure.

Possible reasons driving each of these situations are: the difference in liquidity across markets, and/or the difference in market demands. Based on the data I have, liquidity reason is minor, although it can explain the convergence of the prices. Instead, the consistence of high CDS rates at speculative grade suggests that increasing market demand on default hedging drives up the price and makes CDS more expensive to buy. This also indicates that CDS market is a favorite place for investors with credit exposure at speculative grade.

3.5 Conclusion

According to the discussions in previous sections, several points can be drawn:

1. US Treasury is a better approximation of the implied default-free rate in sovereign CDS market than LIBOR;
2. CDS rates at speculative grade are generally greater than the corresponding yield spreads;
3. Increasing market demand for CDS on sovereigns at lower rating drives CDS up;
4. Liquidity results in price convergence;
5. Rating events causes diverging behavior on CDS and bond markets at speculative grade.

Chapter 4

Relationship Of CDS And Bond Markets

Last section has given a steady analysis on the connection between CDS and bond markets. The dynamic relationship of the two markets is going to be studied in this section through various quantitative methods. Factors determining the price disparity are also examined.

4.1 Analyzing Procedure And Data

Stationarity is a prerequisite to time series analysis for getting stable statistic results. Cointegration relationship provides another stability among various time series, when each time series is not stationary. If cointegration exists, vector error correction method (VECM) is applicable to price discovery study; otherwise, Granger Causality test is adopted. Only if a time series with stationarity or a set of cointegrated time series, can it be used in model

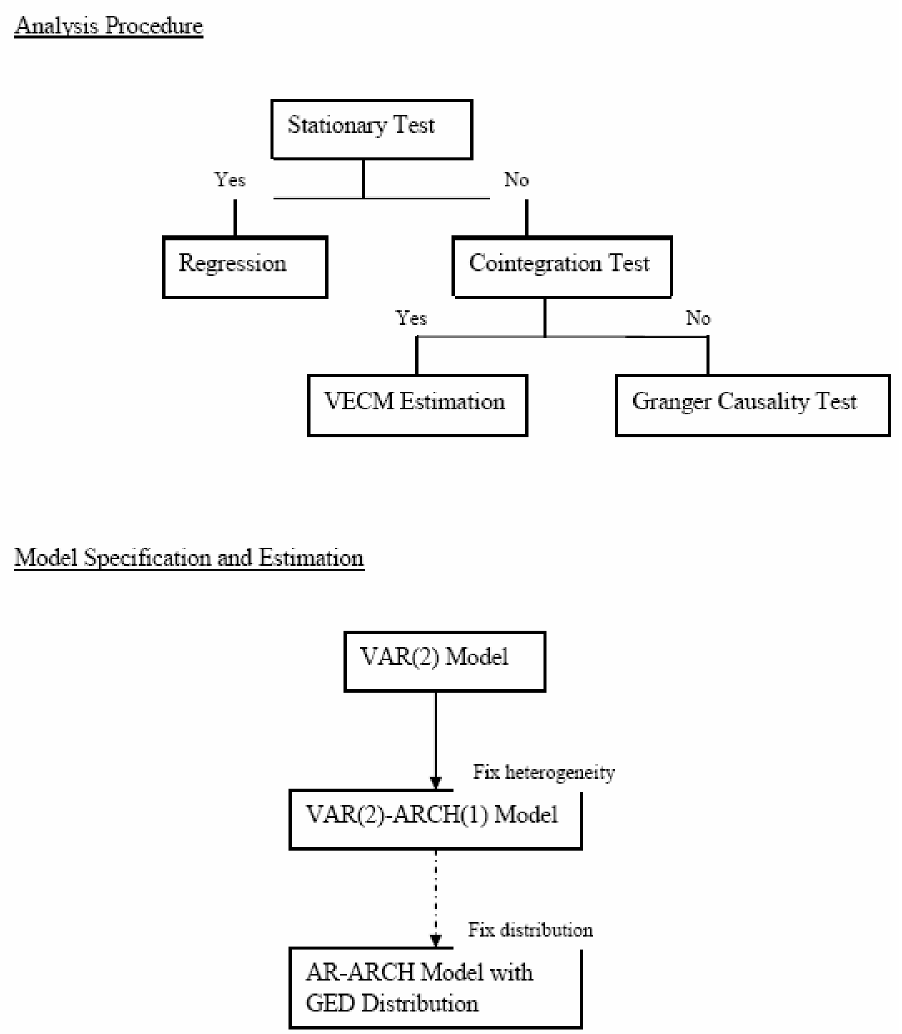

Figure 4.1: Analyzing Procedure

estimation and prediction.

Model structures are also gradually specified by dealing with the conflicts of regressed data to the model assumptions. The final model setting is used for prediction of the credit price disparity. Regressions are carried out per sovereign name, due to the large variety of rating grades among the sampled sovereigns. Their levels of credit deterioration rated vary from grade A for Korea to grade D for Argentina. The common results across these samples are going to be used as market-wide features.

The observations used in this chapter are the same data set used in previous chapter, which are daily data provided by an anonymous broker.

4.2 Vector Autoregressive Models(VAR)

To study the dynamic relationship between CDS rates and yield spreads, first, I use Vector Autoregressive Model(VAR) to function the lag effects and cross lag effects on each of the two credit series in the vector variable(cds_t,ysp_t)'. Weak stationarity is the sufficient and necessary condition for the use of VAR models, which will be examined in the following section using stationary and cointegration tests.

A VAR model is written as:

$$\begin{bmatrix} cds_t \\ ysp_t \end{bmatrix} = \begin{bmatrix} \delta_{1t} \\ \delta_{2t} \end{bmatrix} + \sum_{i=1}^{p} \Phi_i \begin{bmatrix} cds_{t-i} \\ ysp_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1_t} \\ \varepsilon_{2_t} \end{bmatrix} \tag{4.1}$$

Where, $\varepsilon_{1_{t-j}}$ and $\varepsilon_{2_{t-j}}$ for $j = 1, 2, \cdots, q$ are independent white noises; Φ_1,Φ_2,$\cdots$, Φ_p are coefficient matrices of the first, second lag, $\cdots$ and p^{th}

lag of the credit vector. Therefore,

$$\Phi_i = \begin{bmatrix} \phi_i^{11} & \phi_i^{12} \\ \phi_i^{21} & \phi_i^{22} \end{bmatrix}, \text{where,} i = 1, 2, \cdots, p.$$

4.2.1 Model Selection

Since VAR estimates are usually sensitive to the length of vector lags in the model, model selection test is needed. The test shows that the valid order of the credit vector for each sovereign varies from 2 to 5 across sovereign samples, with no moving average(MA) term significant beside the autoregressive(AR) terms. Thus, VAR model is proven sufficient to capture the dynamics of the credit vector. In this study, I use VAR(5) in cointegration test to include any possible lag effects; and VAR(2) in regression and parameter estimation, to avoid collinearity and keep structural function parsimonious.

Table 17 lists parameter estimates of all lag terms in VAR(2) specification; by contrast, Table 16 only highlights the lags significant in VAR(5) regression. The performance of VAR(2) and VAR(5) are compared in table 18. Information criterium like AICC and HQC and adjusted R^2 from each of the univariate equations are reported. A model with higher value of adjusted R^2 and lower value of information criteria performs better. The parsimonious specification VAR(2) exceeds VAR(5) in each aspect. To test the possibility of nonlinear correlation between CDS rates and yield spreads, I also regress the VAR with logarithmic variables, and find results similar.

4.2.2 Stationary Test

Methodology

In financial market, time series are usually not stationary. This impede further quantitative studies[1]. Non-stationarity requires data transformation in order to obtain stationary series to be used in quantitative study. The integration for single time series or the cointegration among more time series is the first try.

The stationarity of each credit series and its first order difference are checked. Followed previous studies, the stationarity of the differences of CDS rates and yield spreads–basis spreads, is also tested. Basis spreads can be deemed as a transformation of the two original credit series by multiplying a parameter vector [1,-1]. When basic spread series is stationary, it means the CDS rates and yield spreads can be stably cointegrated. It also means the differences in the two credit prices are not statistically significant and can be ignorable in long-run study.

Stationarity test is implemented through unit root test with two specifications: zero mean and single mean, respectively. The nonparametric method by Augmented Phillips and Perron(1988) is adopted in the test, so that even if there is serial correlation, it will not affect the asymptotic distribution of the test statistic.A time series is non-stationary, when one or more unit roots is found. If the number of unit roots is one, the first difference of the time series will be stationary, and the time series itself is said integration in order 1, denoted as I(1).

[1]Since non-stationary time series can result in unstable statistical and econometric results, and fault conclusions.

Test Result

Table 4.1: Unit Root Tests

Name	Zero CDS	Mean YSP	BSP	Single CDS	Mean YSP	BSP
Argentina	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)*
Egypt	I(1)	I(0)	I(1)	I(1)	I(0)	I(1)
Korea	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Mexico	I(1)	I(1)	I(0)*	I(1)	I(1)	I(0)
Russia	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
South Africa	I(1)	I(1)	I(1)	I(1)	I(0)*	I(0)*
Brazil	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Venezuela	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)*

Note: YSP represents yield spreads; BSP represents basis spreads. * refer to the result with significant coefficient between 1% and 5%.

The numbers of unit root for CDS rates series, yield spreads series, and basis spreads series are reported. The CDS rates of each sovereign and the yield spreads of most sovereigns are none-stationary in themselves, and stationary in their first differences. This accords with previous research. But the yield spreads series in Egypt and South Africa are exceptional stationary. [2] The exception may derive from their less liquid sovereign bonds. Correspondingly, basis spreads series is stationary except for Egypt and South Africa. This indicates that CDS rates and yield spreads are equivalent in a long run for most of the sovereign bonds. Stable cointegration also makes CDS rate and yield spread a stable credit vector which insures its further use.

[2] The stationarity of yield spreads series for South Africa is only observed in single mean specification.

4.2.3 Cointegration Of CDS Rates And Yield Spreads

Cointegration test, proposed by Engle and Granger(1987), examines the linear stationarity among different non-stationary time series. It provides statistical evidence of the dynamic relationship among credit prices in a short run. [3] Using the model selected by MINIC, five cointegration tests for each sovereign name are implemented to check the cointegrating relationship within different structures.

The five cointegrating structures proposed by Johansen(1995a) are as follows:

1. The level data have no deterministic trends and the cointegrating equations do not have intercepts:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Phi_i^* \Delta Y_{t-i} + \epsilon_t,$$

2. The level data have no deterministic trends and the cointegrating equations have intercepts:

$$\Delta Y_t = \alpha(\beta', 1)(Y_{t-1}, 1)' + \sum_{i=1}^{p-1} \Phi_i^* \Delta Y_{t-i} + \epsilon_t.$$

3. The level data have linear trends but the cointegrating equations have only intercepts:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Phi_i^* \Delta Y_{t-i} + \delta_0 + \epsilon_t.$$

[3] In this paper, a short run refers to time intervals within one week; a long run refers to time periods more than three months.

4. The level data and the cointegrating equations have linear trends:

$$\Delta Y_t = \alpha(\beta', \beta_1)(Y_{t-1}, t)' + \sum_{i=1}^{p-1} \Phi_i^* \Delta Y_{t-i} + \delta_0 + \epsilon_t.$$

5. The level data have quadratic trends and the cointegrating equations have linear trends:

$$\Delta Y_t = \alpha(\beta', \beta_1)(Y_{t-1}, t)' + \sum_{i=1}^{p-1} \Phi_i^* \Delta Y_{t-i} + \delta_0 + \delta_1 t + \epsilon_t.$$

Here α refers to the vector $[\alpha_1, \alpha_2]$, and β refers to vector $[1, \beta]$ in a VECM(p) model. Johansen rank test and maximum eigenvalue test are alternative techniques in performing these tests.

Test Results

Cointegration test is used to confirm the stability of credit vector found in stationary test. It can also release more detailed information on the relationship of the two credit premiums. VAR(5) is the model specification. With daily frequent data, the test in VAR(5) setting captures the weekly behavior of the cointegrating relationship. Table 4 is a summary of the cointegrating relations of the credit prices in each sovereign sample. The relation is tested within 5 specifications at a 5% of significance level, and the results using two methodologies: Johansen rank test and Max eigenvalue criteria are both reported.

The overall results support the stable cointegrating relationship between CDS rates and yield spreads which is implied from previous stationary test.

Except Egypt and South Africa, cointegration is observed in all other sovereign samples. However, it is also found that the structure of the cointegrating relationship varies dramatically across these sovereign names. Mexico and Venezuela only satisfies one cointegration specification; while, other names fit in two or more structures. And only pre-default subsample of Argentina can pass the test, since after-default credit prices are divergent, stagnant and illiquid, this breaks their stable relationship[4].

The five cointegration structures are listed in column 3 to 7 in Table 13. The cointegrating relationship in Korea, Russia and Brazil samples is much stronger than the rest of samples, since no intercept and time trend terms are included. Cointegration in the samples of pre-default Argentina and Venezuela requires a intercept term, implying some fixed effect existed in the relationship of two credit prices. The reason is to be investigated in a later section of this study. The cointegration in Mexico sample contains both intercept and time trend, showing weak stability of the relationship.

Another difference between stationary test and cointegration test is the actual significance levels. Results in cointegration test seem less significant. There is an argument that conditional heteroscedasticity can affect cointegration test significantly. It is necessary to be examined to clarify the picture.

[4]Argentina Euro-bonds defaulted in Dec. 2001. Institutes stopped selling CDS contract, instead, they fixed their quotes at very high level to avoid further dealing. On the other side, the defaulted euro-bonds were still traded at deep discount prices, therefore bond yields continued fluctuating. The comovement of CDS rates and yield spreads, then stopped.

4.2.4 Long-Term Equilibrium And Short-Term Disparity

The stationary and cointegration tests in previous subsection have not only proven the validity of model selection, also testified to the dynamic relationship from two time dimensions–a long run and a short run. The stationary test on basis spreads found that the pricing discrepancy between CDS rates and yield spreads is not significant for the sovereigns whose sampled time intervals are more than one year; but significant for the names with time interval less than one year, such as Egypt. This implies that credit pricing discrepancy only exists in a short run; while, in a long run, pricing equilibrium can be obtained for sovereign names.

The cointegration test on the CDS rates and yield spreads have also confirmed the short-term pricing discrepancy. Within a VAR(5) setting, weekly relationship is examined. Only in three out of eight sovereigns, the cointegrating structure has no intercepts and no time trend. For other sovereign samples, Short-term disparity has been observed through intercept terms, time trend term, or the failure of cointegration. Even for the sovereigns where credit prices are cointegrated without extra terms, the cointegrating coefficients are not equal to $[1, -1]$, stating the existence of price disparity [5].

[5] The cointegrating coefficients of the two credit prices in each sample are carried out in the VECM model at the following section. Their values are listed in Table 5

4.3 Price Discovery In CDS And Bond Markets

Price discovery study helps to check whether sovereign CDS market is well developed to transmit innovations of credit risk into its price. As a direct price of credit risk, CDS rates should be able to adjust and fully discover credit price faster than yield spreads, which are implied from bond prices. More demand for CDS contracts will rise only if the market can efficiently price the credit premium and can lead other markets.

4.3.1 Vector Error Correction Model

Model Specification

Vector Error Correction Model(VECM) is a constrained VAR model. Once the cointegrated vector variable is found stationary, and the order of cointegration is one, VEC model can be used to explore the dynamics of co-movement among the time series. VECM is once used to improve longer term forecasting over the unconstrained VAR model. In this study, I use this model to study the weekly price discovery of credit risk between the two markets. The error correction terms is the focus.

A VECM(p) model is written as:

$$\begin{bmatrix} \Delta cds_t \\ \Delta ysp_t \end{bmatrix} = \begin{bmatrix} \delta_{1t} \\ \delta_{2t} \end{bmatrix} + \Pi \begin{bmatrix} cds_{t-1} \\ ysp_{t-1} \end{bmatrix} + \sum_{i=1}^{p-1} \Phi_i^* \begin{bmatrix} \Delta cds_{t-i} \\ \Delta ysp_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1_t} \\ \varepsilon_{2_t} \end{bmatrix}, \tag{4.2}$$

where,

$$\Pi = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \begin{bmatrix} 1 & -\beta \end{bmatrix}.$$

Then the model can also be written as:

$$\begin{bmatrix} \Delta cds_t \\ \Delta ysp_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} (cds_{t-1} - \lambda - \beta ysp_{t-1}) + \sum_{i=1}^{p-1} \Phi_i^* \begin{bmatrix} \Delta cds_{t-i} \\ \Delta ysp_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1_t} \\ \varepsilon_{2_t} \end{bmatrix} \tag{4.3}$$

Two parts are constituted in a VECM model: the term with the first lag of the vector variable, called 'error correction term'; and the term with lags of the first difference of the vector variable. The cointegrating coefficients of CDS rates and yield spreads are normalized into the vector [1,-β], which is embedded in error correction term. The prior estimate of β is 1, showing the uniform of credit prices in different markets. When $\lambda = 0, \beta = 1$, the first term in the model equals to the first lag of basis spreads. Estimates in the vector $[\alpha_1, \alpha_2]\prime$ are called 'adjustment coefficients', measuring the speed of error correction in price disparity. [-,+] are desired signs of the two adjustment coefficients for the purpose of disparity diminishing. A negative α_1 means that bond market is leading the credit price change, and CDS market will adjust its price to the change in yield spreads. On the other hand, a positive α_2 represents the leading role of CDS market, followed by the adjustment in bond market. If both adjustment coefficients are significant in their right signs, the relative magnitude of the two coefficients will reveal who is the leading market.

Estimates Of The Correction Terms

p in equation 4.3 is 5, to include the first four time lags of the first difference of the credit vector, generated by the first five lags of the credit vector. VECM(5) is model specification in corresponding to VAR(5) used in previous test. Regressors without time trend are both estimated. Table 5 reports the coefficient estimates of α_1, α_2, the time trend and β , since only the first part of the VECM model is of interest. Because there is no cointegration in the samples of Egypt and South Africa, their estimates are not reported here.

Table 14 shows that β estimate for each sovereign is persistently, significantly different from 1, its value is in a range of 0.60 to 1.72. This means that CDS rates and yield spreads are not equal in a very short run, but their values are very close. This discrepancy coincides with the findings in previous tests. Estimate of time trend is significantly negative in the samples whose credit prices are cointegrated with intercept and trend. The negativity indicates diminishing discrepancy over time as the CDS market was more mature and more developed.

None of the sovereign samples possess simultaneously significant estimates of the two αs. The leading market in the price discovery is simply found through the significant estimate of α. Argentina, Mexico and Russia samples show the leading role of bond market via the significant negativity of their α_1 estimates. While, significantly positive α_2 estimate is found in samples of Korea and Venezuela, describing the leadership of CDS market. Brazil has much weaker evidence of CDS market domination.

The analysis of VECM estimates has proven that CDS rates and yield spreads are very close but not equivalent. However the price discovery process in the two markets varies by sovereign names. The discovery pattern may also change over time for the same sovereign name. The reasons or determinants behind this need a further investigation, which is beyond the scope of this study.

4.3.2 Granger Causality Between The Two Markets

Previous price discovery analysis are insufficient because the validity of VECM estimation is contingent to the cointegration relationship, which does not apply to every sovereign borrower. As an extension of the research, Granger causality test in VAR setting is cited. Introduced by Granger in 1969, this test has been widely used in macroeconomic literature, due to its unrestricted estimation and straight-forward explanation.

In a VAR(p) model 4.1, ϕ_t^{12} and ϕ_t^{21} represent coefficients of cross terms, where ϕ_t^{12} indicates the impact of the t^{th} lag of yield spreads on current CDS rates and ϕ_t^{21} shows the influence of the t^{th} lag of CDS rates on current yield spreads. Given a VAR(5) model, the null hypothesis of causality test is a joint hypothesis that all of the coefficients of the cross effect terms are simultaneously equal to zero. To test yield spreads do not Granger cause CDS rates, the hypothesis H_0 is,

$$\phi_1^{12} = \phi_2^{12} = \cdots = \phi_5^{12} = 0.$$

To test whether CDS rates do not Granger Cause yield spreads,the hypothesis H_0 is,

$$\phi_1^{21} = \phi_2^{21} = \cdots = \phi_5^{21} = 0.$$

Note that Granger causality describes a statistical correlation, but does not conclude any economic or financial causality. It is useful in forecasting, since it directly describes the predictive power of cross lags besides the explanatory power of its autoregressive terms[6]. However, its accuracy may be greatly affected when the underlying distribution of the time series is not normal. Some scholars have attempted other types of the Granger Causality test with some improvement, but I am still using the original Granger causality test.

Testing Result:

The non-causality hypotheses in two directions are tested respectively. The results are found sensitive to the order of VAR model. To obtain a full view of the statistical causality, I use four specifications: VAR(1),VAR(5),VAR(10) and VAR(20). With daily frequent observations, VAR(5) tracks weekly causality of the two credit prices and VAR(20) tracks its behavior persistent within one month. [7] Table 15 reports the Wald statistics for each of the hypothesis. The third and fifth columns are values of the probability related to each Wald statistics. The smaller the probability value, the more significant the causality.

The testing results are almost the same as those of VECM estimation, except for the cases of Brazil and Venezuela. According to Wald statistics,

[6] Autoregressive terms refer to the time lags of the left-hand-side variable in a model.

[7] There are at most five trading days each week and twenty two trading days each month. Only trading date data are included in each sample.

bond market dominates CDS market for more sovereigns, and causal relationship between CDS rates and yield spreads is still not found in Egypt and South Africa. The difference of the two tests is the leading market testified in Brazil and Venezuela, which is CDS market in VECM estimation, but bond market in causality test. Yield spreads statistically cause CDS rates in five sovereign borrowers, CDS rates cause yield spreads only in two borrowers. The statistical causality works in one direction for most sovereigns, but in both directions for Argentina. Korea becomes the only sovereign with CDS market dominating the price discovery. Wald statistics also show evidences of price discovery in CDS market in Argentina within all settings and Venezuela within VAR(1) and VAR(5) settings. But their corresponding probability values are less significant than those in the causality test of bond market to CDS market. For the four settings of the tests in each sovereign sample, consistent pattern of price discovery exists for most sovereign names except for Venezuela and Russia, along with the different values of Wald statistics and levels of significance. The probability values of the Wald statistics indicate that VAR(5) specification has the most distinguished significance level whenever causality is found. The significance level diminishes as longer length of time lags included in VAR model.

Overall, bond market dominates the price discovery of credit risk within a short period ranging from one day to one month. This finding is in contradiction with previous literature on the credit risk of corporate bonds. This may be addressed by the gap between sovereign CDS and corporate CDS markets. Since the two segment markets have different structures of market participants, liquidity and levels of market efficiency.

4.3.3 Evidences In Model Estimation

The pattern of price discovery within three trading days is clearly observed in VAR(2) estimation. This is used as evidence in support of the findings in previous section.

In Table 17, the variation of yield spreads is basically explained by its own lags. The estimate of the first autoregressive term is positive and significant, with a value ranging from 0.60 to 1.18; only one sovereign sample possesses significant cross effect from CDS rates on yield spreads. These indicate that yield spreads are exogenous to CDS rates. In contrast, CDS rates are more affected by the cross terms. The coefficient estimates of cross lags are significant, the second cross lag somehow shows more significant than the second autoregressive term. Compared to yield spreads, CDS rates are more endogenous, and affected by past yield spreads.

All of the three quantitative examinations in this section have confirmed that sovereign bond market contains the most innovative information of credit risk in a short run, and leads the price changes in CDS market.

4.4 A Remedy For The Problem Of Heterogeneity

Significant heteroscedasticity widely exists in the residual diagnostics of VAR(2) Regression. The normality test on the residuals also fails. This violates the normality assumption in maximum likelihood estimation method, and results in quasi-maximum likelihood(QML) estimation. Maximum likelihood estimation(MLE) gives the best estimation, but QML estimators are less efficient. Based on the coexistence of heterogeneity and the failure of normality test, I will first fix heterogeneity to see if the non-normality just comes from the heterogeneity, or also from the misidentification of underlying distribution.

4.4.1 Multivariate GARCH Model

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is a general tool to fit heterogeneity. Using VAR(2) as the main model, a multivariate-GARCH variance model is added. The overall is called VAR-GARCH model, first proposed by Engle and Kroner (1995). In a multivariate GARCH model the conditional error term is assumed to be multi-normal, although the unconditional error term is not normal. It is described as:

$$\epsilon_t / I_{t-1} \sim N(0, H_t)$$

H_t is the conditional variance-covariance matrix of the k-dimensional random vector ϵ_t. The multivariate GARCH model is then written as:

$$H_t = C_0' C_0 + \sum_{i=1}^{q} A_i' \epsilon_{t-i} \epsilon_{t-i}' A_i + \sum_{i=1}^{p} G_i' H_{t-i} G_i,$$

where C_0, A_i and G_i are $k \times k$ parameter matrices, and C_0 is an upper triangular matrix.

A VAR(2)-ARCH(1) Specification

Compared to univariate GARCH model, multivariate GARCH estimation is both data consuming and time consuming. ARCH(1) and ARCH(1)-Mean models are adopted among the variety of multivariate GARCH specifications to balance the efficiency and accuracy.

Given the bivariate VAR setting, The BEKK (Baba, Engle, Kraft and Kroner (1991)) representation of Bivariate ARCH(1) is:

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = C_0'C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \epsilon_{1,t}^2 & \epsilon_{1,t-1}\epsilon_{2,t-1} \\ \epsilon_{2,t-1}\epsilon_{1,t-1} & \epsilon_{2,t}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \tag{4.4}$$

The three corresponding univariate representations are:

$$h_{11,t} = c_1 + a_{11}^2\epsilon_{1,t-1}^2 + 2a_{11}a_{21}\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{21}^2\epsilon_{2,t-1}^2, \tag{4.5}$$

$$h_{12,t} = c_2 + a_{11}a_{12}\epsilon_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{21}a_{22}\epsilon_{2,t-1}^2, \tag{4.6}$$

$$h_{22,t} = c_3 + a_{12}^2\epsilon_{1,t-1}^2 + 2a_{12}a_{22}\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{22}^2\epsilon_{2,t-1}^2. \tag{4.7}$$

Here, $h_{11,t}$ represents the conditional variance of CDS rates at time t, $h_{22,t}$ represents the conditional variance of yield spreads at time t, and $h_{12,t}$ is the covariance of CDS rates and yield spreads at time t. Both conditional variance and covariance are determined by the combination of the four a parameters, in addition to error terms. a_{12} and a_{21} describe how the two conditional variances are related. When a_{21} equals zero, equation 5 will become an univariate ARCH(1) model, and the variance of CDS rates will not depend on past shocks in yield spreads. When a_{12} equals zero, the variance of yield spreads will not be affected by past shocks in CDS rates. If both a_{12} and a_{12} simultaneously equal zero, bivariate ARCH model will be more like the sum of two univariate ARCH models, regardless whether the covariance is constant or not. The two credit series are correlated through their variances unless all the a parameters equal zero simultaneously. The disturbance vector ϵ_t is assumed conditionally normal given the information at time t-1.

Besides ARCH(1) specification, ARCH-M model is an useful tool to examine the impact of conditional variances H_t on their conditional mean Y_t. A VAR(2)-GARCH(1)-M is written as:

$$Y_t = \delta + \sum_{i=1}^{2} \Phi_i Y_{y-j} + \Lambda h_t + \epsilon_t,$$

$$H_t = C_0' C_0 + A_i' \epsilon_{t-1} \epsilon_{t-1}' A_i;$$

where h_t is a vectorized representation of H_t, shown as $(h_{11,t}\ h_{12,t}\ h_{22,t})'$. Λ is a $k \times k(k+1)/2$ parameter matrix. k is the dimension of the vector variable Y_t, equals 2 for the credit vector.

Estimates In Mean Equation

Table 19-21 includes estimates in VAR(2)-ARCH(1) model. Estimates from ARCH-M model are not reported since the impacts of conditional variances on the mean values of the credit vector are simultaneously insignificant. Egypt and South Africa are exempted from VAR and VAR-ARCH estimations, due to their failures in cointegration test.

Table 19 lists estimates in the main model. Compared with original VAR(2) estimation, all estimates become more significant, especially the estimates of constant term in each sample. Constant estimate is now significant in all sovereigns; but only in Venezuela sample in VAR(2) regression. Looking at the credit ratings of the 6 sovereigns, I find that the highly rated sovereigns accompany with smaller constant values, where lowly rated names have greater constants. This implies that a credit-related factor may be hidden in the constant term.

The significance levels of coefficient estimates are also largely improved. The cross effects of yield spreads on CDS rates become significant in the cases of Argentina, Mexico, Brazil and Venezuela; and the influence of CDS rates on yield spreads is only found significant in Argentina. The magnitudes of estimates are also different from VAR regression. In Korea and Russia, the relationship of CDS rates and yield spreads is fully represented by the correlation of their variance. Thus, the cross terms in main equation become insignificant and unimportant, and the cross terms in variance equation are very significant. This transition reveals an additional interaction channel between CDS and bond markets, and inspires more complex patterns of their correlation. It also proves that multivariate ARCH estimation is an important supplementary to the comparative studies on credit prices. The most disadvantage of VAR-ARCH model is that it will lose a large amount of its degree of freedom as ARCH regressors are added. VAR model still exceed VAR-ARCH model in estimating and predicting.

Estimates In Variance Equations

Most of Bivariate ARCH estimates are significant. This means that CDS rates and yield spreads are interacted not only through their values, also through the correlation of the two variances and through their covariance[8]. The estimators of the bivariate ARCH model are reported in Table 20 and Table 21. The significant estimates of constant terms for each sample are strictly positive, which is one guarantee of positivity variance. There are at least one constant term in each sovereign that is significantly different from zero. The significance of the four a terms vary by sample. The cross terms a_{12} and a_{21} are the most important pair of terms in the model, since they describe the correlation of the two variances. Except for Mexico, at least one of the two cross terms is significant for the samples. Brazil is the only sovereign sample where a_{11} and a_{22} are both indifferent from zero.

In sum, ARCH-VAR regression has given a richer explanation on the relationship of CDS rates and yield spreads, and examined more interacting channels. It exceeds the original VAR analysis model by exploring more information. According to the ARCH-VAR regression, CDS rates and yield

[8]Covariance indicates the correlation of their error terms, where the correlation of the variances means that the value of each variance is affected by the past errors of the other variable.

spreads are connected, through their values in Mexico sample, but through both their values and variances in other samples. ARCH-VAR regression is also an easier tool to implement than the stochastic models used in other research.

4.4.2 The Efficiency Of QML Estimation In VAR-ARCH Model

By removing the heterogeneity problem via ARCH model, normality of the conditional residuals are reexamined. Based on the residual diagnostic in VAR-ARCH regression, the residuals are still not normal. So, heterogeneity is not the only reason for the non-normality. The underlying distribution of the conditional error terms in the credit vector may follow non-normal distribution. Meanwhile, the efficiency of the estimators in VAR-ARCH is worth discussion, since they are no longer the best ML estimators.

Gonzalez-Rivera et al(1995) argue that efficiency losses depend on departures from the normality assumption; if the underlying distribution is far from normal, efficiency losses can be huge.[9] However, previous literature such as Tuncer (1994, 2000) and Bauwens et al(1995) have proven the strong consistency of QML estimators in a simple multivariate-ARCH model. Ling and McAleer (2003) conclude the asymptotic normality in a VARMA-GARCH model requiring only the existence of the second-order moment of the unconditional errors, and a finite fourth-order moment of the conditional errors. These researches confirm the validity and feasibility of VAR-ARCH estima-

[9]A severe efficiency loss leads to overestimated variances, underestimated t values, and the acceptance of wrong hypotheses.

tions.

4.5 Economic Factors Driving Price Disparity

Previous sections have utilized a variety of tools in proving the short-term relationship between CDS rates and yield spreads, and their long-term equilibrium, i.e. β equals one and α equals zero. Since price disparity is persistent in short run for each sovereign sample, it is worth investigating for a better understanding of the dynamic relationship. The determinants of price disparity are required for the purpose of prediction used in arbitrage trade and hedging strategies.

I use basis spreads to measure the price disparity between yield spreads and CDS rates. Economic factors of credit risk cited in previous researches are tested in the regression of basis spreads.

4.5.1 Proxies Of Economic Factors

Credit Quality

Rating grade reflects the average default probability of a borrower's debt given a certain period. It is used as a proxy of default probability. Since default probability is the basic factor in credit risk valuation, its impacts on CDS rates and yield spreads should be indifferent, and not lead price disparity. But if CDS and bond markets have big difference in market efficiency, the change of credit rating will have a temperate effect on price disparity.

The effect can be negative or positive.

A variable 'Rate' is generated with values from 1 to 10 corresponding to rating grades from D to AAA. Fractions like one-third or two-thirds refer to subgrades within each category. Since the variable is a linear instrument, it might not be able to capture the nonlinear impact, and might encounter an estimation bias.

Credit Event

Previous studies argues that credit events especially downgrade events have significant impact on credit pricing. Here I want to see if it has an impact on credit price disparity. Four dummies are generated to track its influence within the three months around an event, two months before the event and one month afterward. The three months are divided into four periods, and represented by four dummies. Dumb3160 measures the time interval from 60 to 31 days before an event; Dumb0130 from 30 days to one day before that date; Duma0010 from 1 to 10 days after the event; Duma1130 is from 11 to 30 days after the event. Coefficient estimates of the four dummies explain how the price disparity changes upon a credit event. If the sign of the estimate is positive, the pricing gap enlarges during the relevant period. Given an upgrade event, the positivity indicates that CDS rates decrease more than yield spreads; for a downgrade event, it means that yield spreads increase more than CDS rates. If the sign is negative, the converse holds.

CDS Rates Liquidity

Liquidity premium is the second important factor in credit pricing. liquidity premium in CDS rates might be even greater than other credit prices, since the market is newly developed. From the sovereign samples, CDS rate quotes appear very illiquid. Quotes can stay at the same value for a whole week. This is partially because 55% of end-users of CDS products are banks, who usually hold a position without trading until maturity, according to the market survey tabulated in Table 1.

To examine the impact of CDS liquidity on price disparity, I create a liquidity ratio by computing the ratio of the number of quote changes to total number of quotes before time t. The ratio is equal to 1 if CDS quotes fluctuate continuously, and less than 1 if quotes stop changing at least one trading date. It also should be known that liquidity ratio with value 1 does not necessarily imply there are active trades at every date. Because CDS contracts are sometimes bought and sold by the same market maker to keep them tradable at reasonable price levels. So, the liquidity ratio I generate might undervalue the actual liquidity problem in CDS market.

Macro Factor 1– Level Of Yield Curve

10-year treasury rate and its square are employed to test whether CDS rates and yield spreads are reacting differently to the change of yield curve. The square term is to examine its nonlinear impact.

Macro Factor 2– Slope Of Yield Curve

The slope change of yield curve can affect the credit pricing. Its impact on price disparity need to be examined. The slope of the yield curve is approximately equal to the difference of 10-year and 2-year treasury yields.

4.5.2 ARCH Family Given GED Distribution

As a stationary variable, basis spreads is able to be studied via model regression. To find the explanatory powers of each individual and different groups of variables, four univariate ARCH models are constructed by combinations of two main equations and two ARCH equations. The two main equations are written as:

$$Y_t = \alpha + X_t' B + \epsilon_t; \tag{4.8}$$

$$Y_t = \alpha + \gamma_1 Y_{t-1} + \gamma_2 Y_{t-2} + X_t' B + \epsilon_t. \tag{4.9}$$

X is a 9×1 exogenous vector if credit variables included, or a 4×1 vector if credit variables excluded. Credit variables refer to variable 'Rate' and four dummies[10]. The first two autoregressive terms of basis spreads are added in the second main equation in order to improve the overall predictive performance. The two ARCH models are written as:

$$\epsilon_t = \sqrt{h_t}\omega_t, \tag{4.10}$$

ARCH(1):

$$h_t = c + a\epsilon_{t-1}^2; \tag{4.11}$$

[10]If there is no credit event occurred during the sampled period, the value of 'Rate' will be a constant. It have to be dropped from the model to avoid collinearity, if the model has an constant term. So, 'Rate' will be dropped with the four dummies when there is no credit event.

ARCH(1)-X:

$$h_t = c + a\epsilon_{t-1}^2 + \rho LIQ_t. \tag{4.12}$$

The second ARCH equation is a special design to test the impact of CDS illiquidity on the volatility of basis spreads, in addition to its impact on the value of basis spreads.

With the exception of the newly added exogenous vector, the main structure of these specifications is a univariate representative of the VAR-ARCH model used in previous section. The purpose is to keep the whole study consistent. Generalized error distribution(GED) is used to fit the non-normality distribution observed in previous VAR-ARCH regression. The significant test of the GED parameter is reported in each regression. Model performance is compared by information criteria AIC, adjusted R square, and log likelihood ratio.

4.5.3 Model Estimation

Table 22 to Table 27 list the regression results for each sovereign sample. The first part of each table contains estimates in the main equation; the second part has estimates in the variance equation, where the GED distribution parameter ν is also reported; the model selection criteria are in the last part. The pre-default sample of Argentina includes observations until Nov.19, 2001. Egypt and South Africa are exempted from all estimations, due to their failures in the stationary test of basis spreads.

Overall Significance And Model Comparison

All regressions are significant. According to the adjusted R square, the exogenous vector– regressors other than the autoregressive terms, explain a total of 43% to 75% variations in basis spreads; with AR components the overall explanatory power increases by 15% to 36%. AIC and log likelihood give similar confirmation of the model selection. So I use AR-ARCH specification to predict the price disparity, and us ARCH model to track its determinants.

Significance Of Individual Factor

Credit Variables

For the six regressed sovereign samples, five of them contain credit events and changes of rating in the sampled period. Coefficient estimate of Rate is significant and negative in 3 sovereigns: Argentina, Korea and Russia. These three sovereigns experienced 2 to 6 monotonic credit changes during the sampled period. Negativity indicates that an increase of credit quality decreases the price disparity. Brazil and Mexico have 2 and 1 credit events respectively, 'Rate' is more collinear with constant term, the coefficient estimate of Rate is therefore insignificant [11].

The significance of the four credit dummies vary by sample. DUMB0130 is the most significant period. Its coefficient estimate is negative in 4 samples. This means that CDS and bond markets have started to include the information of an upcoming event into their prices one month before its announcement, and the price discovery process in the two markets are differ-

[11] The 2 credit changes in Brazil are in the opposite directions and partially canceled. The values of 'Rate' closes to a constant.

ent. The price disparity has temperately shrunk due to the different discovery paces in the two markets. DUMA1130 has the least significance among the four dummies, showing that credit events no longer affect the price disparity or credit pricing 11 days after the announcement.

CDS Liquidity

The impact of CDS liquidity on basis spreads is examined in both main equation and variance equation. In ARCH equation, LIQ is significant in 5 names. It has a negative sign in 4 names and has a positive sign in one. The negativity means that increasing CDS liquidity will tender the volatility in the price disparity, and make the relationship between CDS rates and yield spreads more stable. The sign of LIQ in main equation is consistently positive for all sovereigns. This matches with the prior estimation, because the increase of liquidity in CDS reduces its liquidity premium and decreases the value of CDS, and thus enlarges the price disparity. [12] When using LIQ as the only regressor, it can explain 20% of total variation.

Macro Factors

YR10 and its square are significant in all samples. Their signs vary by sample, but YR10 always has a sign opposite to its squared term. It means that the impact of yield curve on basis spreads increases at a decreasing rate as the value of YR10 increases. The estimate of yield curve slope is significant in 5 out of 6 sovereigns. The impacts of these macro factors indicate the

[12] Basis spreads equal yield spreads minus CDS rates. When CDS rates are decreasing, basis spreads will increase holding yield spreads constant.

structural differences of the pricing systems in the two markets.

GED Parameter Estimate

GED parameter estimate ν is very significant. Except pre-default Argentina, its value is above 2 and less than 4. ν in pre-default Argentina sample is less than 1. These estimates indicate that the distribution of the underlying error term in basis spreads is far from normal, or student-t distribution. Since the distribution is normal if ν equals to 2, and t distribution has a ν value larger than 1 and less than 2. The values of the estimates also show that the underlying distribution for each sample may be greatly various, and none of them is leptokurtic, which is usually observed in previous research. These phenomena ask for a further study on the components in the error term of the model.

In summary, CDS liquidity, credit quality and its change are important factors to both credit pricing and the price disparity of different credit prices. The increase of liquidity in CDS products has double impact on basis spreads. It will reduce its volatility, but enlarge its value. Macro factors in affecting credit prices also contribute to the change in credit price disparity. The tested determinants can explain about a half of the variation in price disparity. Along with AR(2) terms, they can be used in predicting price disparity and correction in the future.

4.5.4 Latent Common Factor Diagnostic

There are more economic factors discussed in previous research than what I chose. They may carry extra explanatory power and be ignored in my study. To test for the existence of these latent variables, Principle Component Analysis(PCA) is applied on the residuals of AR-ARCH-X regression. This method is also used by Litterman et al(1991), Steeley (1990) and Daniels et al(2004) in yield curve analysis.

The test results are shown in Table 28. Two hypotheses are examined: (1)no common factor; (2) one common factor is sufficient. Probability values of the two Chi-square statistics indicate that the first hypothesis is rejected and the second one is not rejected. The combined result is that there is at least one latent variable across samples, and using one latent variable is sufficient in describing the commonalities among the seven sets of residuals.[13] A summary of the PCA analysis is found in Table 29. The first part of the table lists descriptive statistics and PCA estimates; the second part shows pairwise correlations between two sovereignsŕesiduals. The coefficient estimate of the latent factor varies from 0.21 to 0.68. The proportion of residuals explained by the latent variable differs from 0.045 in Venezuela to 0.46 in Mexico. The latent variable can either be a market-level factor or another macro factor.

[13]I drop the sample of Argentina, since there is no common time span between pre-default Argentina data and other sovereign data. Argentina defaulted in Dec. 2001, its pre-default period ends in Nov. 2001, where the common period of other samples starts from Dec.18, 2001. I still keep Egypt and South Africa samples as references, so they are also included here to confirm the validity of the latent common factor.

4.6 Conclusion

The dynamic relationship of sovereign CDS and bond markets has been analyzed in different dimensions. The variety of the credit qualities over the sampled sovereigns makes the firm-level features of the dynamic relationship more obvious. Given the limit of sovereign names and the short time span of the market data, it becomes more difficult to generalize the market-level properties of the relationship. The conclusion is therefore, only based on the eight sovereign samples during year 2000 to year 2002.

According to the results in above sections, the equilibrium between CDS rates and yield spreads can only hold in a long run in sovereign cases. Price discovery is found in both markets but traditional bond market comprises the majority. In most samples, the leading role can persist for one month, implying less liquidity and efficiency in sovereign CDS products.

Besides presenting findings on the dynamic relationship of the two markets, this paper extends previous study on CDS liquidity to address its multi-impact on credit price disparity, and provides a new instrument to quantify the degree of illiquidity in CDS products. Even though the instrument is still primary, the significance of CDS liquidity effect on price disparity is widely found. The impact is both observed on the values and the volatilities of price disparity. Given the instrument, the explanatory power of CDS liquidity can explain up to 20% of variation in basis spreads. Other factors such as yield curve, credit events and credit quality also are significantly affecting the magnitude of price disparity.

This study also contributes to the emphasis of model comparison and specification, and the improvement of model prediction. ARCH-X and multivariate ARCH are found to be very useful when accompanied with autoregressive models. GED distribution is better fitted to residuals in univariate ARCH estimations.

Table 2: Data Interpolation Record–(07/22/2004)

country	bond1	maturity1	bond2	maturity2	bond3	maturity3
Argentina	$Arge-FRB$	3/29/2005	$Arge-09$	4/7/2009	—	—
Brazil	$Brazil-04$	4/15/2004	$Brazil-07$	7/26/2007	$Brazil-09$	10/15/2009
China	$China-04$		$China-08$	12/15/2008	$China-11$	5/23/2011
Egypt	$Egypt-06$	7/11/2006	$Egypt-11$	7/11/2011	—	—
Israel	$IsraelE-06$	6/16/2006	$Israel-10$	3/15/2010	—	—
Korea	$KDB06$	5/15/2006	$Kor-08$	4/15/2008	—	—
Mexico	$Mex-05$	4/6/2005	$Mex-07$	1/15/2007	$Mex-11$	1/14/2011
Russia	$RUS-03$	6/10/2003	$RUS-07$	6/26/2007	$RUS-10$	3/31/2010
South Africa	$SOAF-06$	10/17/2006	$SOAF-09$	5/19/2009	—	—
Venezuela	$Vene-07$	6/18/2007	$Vene-NMB-05$	12/18/2005	—	—

Table 3: Regressions On Various Benchmarks (Korea)

Constant	-0.0421	0.11932 (0.324)	-0.6695	-0.5189
SE of Constant	0.14548	0.1208	0.13239	0.13268
Coef of r_T	1.15126	1.13866	———	———
SE of coef.	0.03305	0.02726	———	———
Coef of r_S	———	———	1.11552	1.09416
SE of coef.	———	———	0.02594	0.02556
Coef of q	———	-36.41	———	-14.383
SE of coef	———	3.36867	———	3.35789
SE of Residual	0.18986	0.15645	0.15842	0.15309
Adjusted R^2	0.8313	0.8854	0.8825	0.8903

Table 4: Regressions On Different Benchmarks (Mexico)

Constant	-0.9802	-0.9415	0.51655	0.58428
SE of Constant	0.1359	0.12073	0.17595	0.17806
Coef1 of r_T	1.27576	1.27781	———-	———-
SE of coef1	0.03024	0.02685	———-	———
Coef2 of r_S	———	———	0.81101	0.80146
SE of coef2	———-	———	0.03369	0.03383
Coef3 of q	———	-66.99	———	-25.312
SE of coef3	———	7.05664	———	12.1458
SE of Residual	0.20028	0.17783	0.30479	0.30327
Adjusted R^2	0.8423	0.8757	0.6347	0.6384

Table 5: Regressions On Various Benchmarks (Brazil)

Constant	-3.43403	-3.57299	-2.842635	-1.91951
SE of Constant	0.100982	0.20316	0.1259903	0.230524
Coef of r_T	1.568426	1.591228	———	———
SE of coef.	0.020847	0.035657	———	———
Coef of r_S	———	———	1.241553	1.114136
SE of coef.	———	———	0.0223218	0.034632
Coef of q	———	6.935808	———	-49.6303
SE of coef	———	8.797618	———	10.47901
SE of Residual	0.28953	0.28965	0.38019	0.37145
Adjusted R^2	0.9262	0.9261	0.8727	0.8785

Table 6: Regressions On r_T (Russia)

		total change	rating change	outlook change
Constant	-1.57786	-1.81975	-1.791772	-1.06155
SE of Cons	0.181087	0.202933	0.1829831	0.206911
Coef of r_T	1.332425	1.361092	1.344793	1.236896
SE of coef	0.03924	0.040517	0.0383731	0.043127
Coef of q	———	9.296025	15.72242	-41.5878
SE of coef	———	3.620474	3.513826	8.755815
SE of Residual	0.36188	0.35919	0.35297	0.35183
Adjusted R^2	0.7554	0.759	0.7673	0.7688

Table 7: Regressions On Various Benchmarks (Venezuela)

Constant	-6.76807	-7.06632	-3.808003	-3.70939
SE of Constant	0.996918	0.985814	0.8929995	0.895296
Coef of r_T	2.305372	2.404267	———	———
SE of coef.	0.224527	0.223211	———	———
Coef of r_S	———	———	1.413709	1.406151
SE of coef	———	———	0.1735201	0.173422
Coef of q	———	-88.3867	———	-37.9842
SE of coef	———	27.96347	———	29.65481
SE of Residual	1.3723	1.3508	1.4476	1.4459
Adjusted R^2	0.2709	0.2936	0.1887	0.1906

Table 8: Regressions On r_T (Argentina)

	Not added	Total change	Rating change	Outlook change
Constant	-70.977	-21.1301	64.25671	-116.47
		(0.159)		
SE of Cons	6.443582	14.97999	13.04487	8.510645
Coef of r_T	13.25201	5.417936	-8.747957	19.58147
		(0.031)		
SE of coef1	1.320765	2.498528	2.237399	1.49632
Coef of q	———	-657.512	-2660.512	1372.015
SE of coef	———	178.9141	230.9909	179.6761
SE of Residual	19.284	19.028	17.011	18.188
Adjusted R^2	0.1771	0.1988	0.3596	0.2679

Table 9: Regressions Of Yield Spreads On CDS Rates

	Pool of Six	Argentina	Egypt	Korea	Mexico	Russia	South Africa
Constant	0.01097	0.019761	0.024375	0.002735	0.000317	-0.0068	0.014213
SE of Cons.	0.001553	0.006671	0.000876	0.000444	0.000697	0.000728	0.002742
Coef of CDS	0.841371	0.830944	0.10169	1.417557	1.111512	1.118144	0.52008
SE of coef	0.005108	0.011664	0.034368	0.049779	0.028763	0.009607	0.141073
SE of Residual	0.05731	0.10821	0.00199	0.00177	0.00223	0.00384	0.00242
Adjusted R^2	0.9422	0.9164	0.07	0.767	0.8176	0.9732	0.0809
No. of obs	1667	464	104	247	334	374	144

Table 10: Regressions Of CDS Rates On Yield Spreads

	Pool of Six	Argentina	Egypt	Korea	Mexico	Russia	South Africa
Constant	-0.00475	0.009595	0.003925	0.000523	0.004108	0.00787	0.015306
SE of Cons	0.001815	0.007745	0.007088	0.000293	0.000521	0.000585	0.001113
Coef of spread	1.119829	1.103044	0.77734	0.541763	0.736038	0.870437	0.16796
SE of coef	0.006798	0.015483	0.262714	0.019025	0.019047	0.007479	0.045559
SE of Residual	0.06612	0.12468	0.00551	0.00109	0.00182	0.00339	0.00137
Adjusted R^2	0.9422	0.9164	0.07	0.767	0.8176	0.9732	0.0809
No. obs	1667	464	104	247	334	374	144

Table 11: Foreign Currency Sovereign Credit Rating History

Sovereign	Date	Long Term/ Outlook/Short Term
Argentina (Republic of)	Feb. 12, 2002	SD/NM/SD
	Nov. 6, 2001	SD/NM/C
	Oct. 30, 2001	CC/Negative/C
	Oct. 9, 2001	CCC+/Negative/C
	Jul. 12, 2001	B-/Negative/C
	Jun. 6, 2001	B/Negative/C
	May. 8, 2001	B/CW-Neg./C
	Mar. 26, 2001	B+/CW-Neg./B
	Mar. 19, 2001	BB-/CW-Neg./B
	Nov. 14, 2000	BB-/Stable/B
	Oct. 31, 2000	BB/CW-Neg./B
	Feb. 10, 2000	BB/Stable/B
	July. 22, 1999	BB/Negative/B
Brazil (Federative Republic of)	Jul. 2, 2002	B+/Negative/B
	Aug. 9, 2001	BB-/Negative/B
	Jan. 3, 2001	BB-/Stable/B
	Feb. 29, 2000	B+/Positive/B
	Nov. 9, 1999	B+/Stable/B
	Jan. 14, 1999	B+/Negative/B
Egypt (Arab Republic of)	May 22, 2002	BB+/Stable/B
	Jun. 22, 2001	BBB-/Negative/A-3
	Jul. 3, 2000	BBB-/Negative/A-3
	Jan. 15, 1997	BBB-/Stable/A-3
Korea (Republic of)	24-Jul-02	A-/Stable/A-2
	Nov. 13, 2001	BBB+/Stable/A-2
	Nov. 11, 1999	BBB/Positive/A-3
	Jan. 25, 1999	BBB-/Positive/A-3
	Jan. 4, 1999	BB+/Positive/B
United Mexican States	Feb. 7, 2002	BBB-/Stable/A-3
	March 10, 2000	BB+/Positive/B
	Sept. 2, 1999	BB/Positive/B
Russian Federation (The)	Dec. 5, 2002	BB/Stable/B
	Jul. 26, 2002	BB-/Stable/B
	Feb. 22, 2002	B+/Positive/B
	Dec. 19, 2001	B+/Stable/B
	Oct. 4, 2001	B/Positive/B
	Jun. 27, 2001	B/Stable/B
	Dec. 8, 2000	B-/Stable/C
	Jul. 27, 2000	SD/NM/SD
	Feb. 15, 2000	SD/NM/SD
	May. 7, 1999	SD/NM/SD
South Africa (Republic of)	7-May-03	BBB/Stable/A-3
	Nov. 11, 1999	BBB/Positive/A-3
	Jan. 25, 1999	BBB-/Positive/A-3
	Jan. 4, 1999	BB+/Positive/B
Venezuela (Bolivarian Republic of)	Dec. 13, 2002	CCC+/Negative/C
	Sept. 23, 2002	B-/Negative/C
	Mar. 18, 2002	B/Negative/B
	Feb. 11, 2002	B/CW-Neg./B
	Dec. 21, 1999	B/Stable/B

Table 12: Descriptive Statistics

Group	Variable	Mean	S.D.	Minimum	Maximum	Skewness	Kurtosis	Obs
Argentina	yield spreads	33.51157	37.42618	4.033142	155.3261	1.173613	-0.04544	491
	cds	38.14135	43.53756	4.547808	138	1.140462	-0.24455	
	basis spreads	-4.62978	13.11166	-53.7863	55.32613	-1.08876	5.305478	
	Rate	4.3537678	1.5476253	2	6	-0.4715357	-1.3825196	
	liq	0.8239339	0.0938925	0.6367347	1	0.4930609	-0.2638666	
Egypt	yield spreads	2.689036	0.203573	2.211331	3.07362	-0.25353	-0.87597	112
	cds	2.471518	0.569014	1.75	3.45	0.580917	-1.29083	
	basis spreads	0.217518	0.545298	-1.02742	1.064164	-0.53614	-0.91422	
	Rate	6.7 0	6.7	6.7	.	.		
	liq	0.2079699	0.1829627	0.0897436	1	2.7960824	8.3341272	
Korea	yield spreads	1.495885	0.364723	0.81427	2.375457	-0.17565	-1.08172	265
	cds	0.864849	0.227772	0.48	1.425	0.13377	-0.52379	
	basis spreads	0.631036	0.19654	0.233156	1.350457	0.69283	0.434702	
	Rate	7.2154717	0.2463873	7	7.7	0.8492459	-0.4209881	
	liq	0.5785268	0.0670085	0.3333333	1	0.6777684	5.0878439	
Mexico	yield spreads	2.681746	0.520128	1.576827	3.755375	-0.17975	-0.92338	355
	cds	2.385859	0.422419	1.58	3.7	0.449099	0.301056	
	basis spreads	0.295887	0.228772	-0.17317	0.906803	0.496747	-0.57025	
	Rate	6.4498592	0.2875353	6.3	7	1.4000007	-0.0402568	
	liq	0.5829937	0.060406	0.3333333	1	1.0479552	12.6335336	
Russia	yield spreads	7.448275	2.346155	3.517659	11.72253	-0.20559	-1.11796	399
	cds	7.2719	2.069718	3.5	10.5	-0.41099	-1.15727	
	basis spreads	0.176375	0.452681	-0.63316	1.622525	0.870722	0.145298	
	Rate	4.8210269	0.4215958	4.3	5.3	-0.2125395	-1.6419186	
	liq	0.5513374	0.1539137	0.2533333	1	0.0070101	-0.2485765	
South Africa	yield spreads	2.433835	0.252606	1.99781	3.156675	0.709316	-0.12357	154
	cds	1.941266	0.141151	1.7	2.15	-0.33245	-1.08364	
	basis spreads	0.492569	0.251067	-0.014	1.256675	0.855329	0.709959	
	Rate	7	0	7	7	.	.	
	liq	0.2467163	0.1009138	0.0666667	1	5.3689582	39.809814	
Brazil	yield spreads	6.935073	1.661436	4.574715	11.75008	0.771719	0.061174	480
	cds	7.423293	1.933592	4.425284	12.8	0.472076	-0.41173	
	basis spreads	-0.48822	0.413506	-1.39864	0.666048	0.390665	-0.32081	
	Rate	5.5295833	0.3325737	4.7	5.7	-1.7956137	1.7286738	
	liq	0.8659711	0.0612846	0.7820513	1	1.3028314	0.4210914	
Venezuela	yield spreads	9.975431	1.490725	7.232924	14.5331	0.702168	0.317307	302
	cds	10.59536	2.544826	7.3	18.5	0.763529	-0.05728	
	basis spreads	-0.61993	1.360823	-4.28739	1.914866	-0.54681	0.227783	
	Rate	5	0	5	5	.	.	
	liq	0.7322617	0.055876	0.5714286	1	1.4438387	7.3684414	

Table 13: Selected (0.05 level) Number of Cointegrating Relations by Model

	Data Trend: Test Type	None No Intercept No Trend	None Intercept No Trend	Linear Intercept No Trend	Linear Intercept Trend	Quadratic Intercept Trend
Arg Pre-Default	Trace	2	1*	2	1*	1
	Max-Eig	2	1*	2	1*	1
Egypt	Trace	0	0	0	0	0
	Max-Eig	0	0	0	0	0
Korea	Trace	1*	0	0	1*	2
	Max-Eig	1*	0	0	1*	2
Mexico	Trace	0	0	0	1*	2
	Max-Eig	0	0	0	1*	2
Russia	Trace	1*	0	1*	2	2
	Max-Eig	1*	1	1*	0	2
South Africa	Trace	0	0	0	0	0
	Max-Eig	0	0	0	0	0
Brazil	Trace	1*	1	1	1*	2
	Max-Eig	1*	1	1	1*	2
Venezuela	Trace	0	0	1*	0	0
	Max-Eig	0	0	0	0	0
(0.1level)	Trace	0	0	1*	0	1
	Max-Eig	0	1	1*	0	1

Note: * refers to the model types used in VECM regressions, the corresponding parameter estimates are reported in the next table.

Table 14: Normalized Co-Integrating Coefficients

Group	Country	β	Time Trend	α_1	α_2
1	Arg Pre-default	-1.151271**		-0.140071**	-0.028452
		(0.02274)		(0.04136)	(0.06028)
		-1.328946**	0.008646	-0.146686**	0.011264
		(0.06642)	(0.00451)	(0.03993)	(0.05844)
3	Korea	-0.599239**		-0.0314	0.134081**
		(0.01781)		(0.02138)	(0.04647)
		-1.332500**	-0.003438**	0.026438	0.274227**
		(0.13316)	(0.00063)	(0.02425)	(0.05044)
4	Mexico	-0.901537**		-0.054803**	-0.011183
		(0.02217)		(0.01888)	(0.02365)
		-1.160036**	-0.002196**	-0.107804**	0.035833
		(0.07353)	(0.00037)	(0.03122)	(0.03923)
5	Russia	-0.960791**		-0.081002**	-0.037488
		(0.01218)		(0.02143)	(0.02603)
		-1.231927**	-0.006785**	-0.05601*	0.035724
		(0.11644)	(0.00237)	(0.02243)	(0.02696)
7	Brazil	-1.080649**		-0.035346	0.043872
		(0.01218)		(0.02682)	(0.02699)
		-1.047529**	-0.001781**	-0.074272	0.088126*
		(0.03367)	(0.0004)	(0.04204)	(0.04234)
8	Venezuela	-1.724827**		0.004884	0.056683**
		(0.18987)		(0.02409)	(0.01685)
		-1.520698**	-0.004947	0.004902	0.067584**
		(0.19949)	(0.00342)	(0.02734)	(0.01909)

Note: Standard errors of estimates are reported in parentheses. ** and * refer to confidence levels of 99% and 95% respectively.

Table 15: Pairwise Granger Causality Tests

Name	Lags	YSP do not Cause CDS		CDS do not Cause YSP		D.F.
Pre-default	1	85.4478**	2.40E-18	1.15888	0.28244	352
	5	43.1284**	2.60E-34	5.56458**	6.10E-05	348
	10	20.1352**	7.40E-29	2.88457**	0.00183	343
	20	12.3036**	1.90E-28	3.22464**	7.10E-06	333
Korea	1	0.51574	0.47331	15.108**	0.00013	264
	5	0.88647	0.49070	2.93682*	0.01352	260
	10	1.06498	0.39025	3.22382**	0.00065	255
	20	1.01283	0.44852	2.63251**	0.00032	245
Mexico	1	22.598**	2.90E-06	2.27741	0.13217	354
	5	17.5322**	1.9E-15	0.85344	0.51272	350
	10	8.75189**	1.00E-12	0.96524	0.4737	345
	20	4.58566**	1.70E-09	0.98816	0.47644	335
Russia	1	39.6504**	7.90E-10	1.71934	0.19052	408
	5	11.537**	2.10E-10	2.43649*	0.0342	404
	10	5.8432**	3.30E-08	1.29014	0.23393	399
	20	3.10281**	1.20E-05	1.14577	0.30071	389
Brazil	1	10.6612**	0.00117	2.98605	0.08463	479
	5	21.3523**	3.0E-19	1.52766	0.17967	475
	10	11.6361**	7.2E-18	1.09536	0.36393	470
	20	6.44164**	2.7E-15	1.07638	0.37166	460
Venezuela	1	0.2791	0.59768	8.52587**	0.00377	301
	5	4.36676**	0.00076	3.00249*	0.01169	297
	10	2.59716**	0.00504	1.56328	0.11745	292
	20	1.86449*	0.01563	1.07784	0.37356	282

Note: ** and * refer to confidence levels of 99% and 95% respectively. In terms of daily trading date, 5 lags describe the impact of previous week, 20 lags represent impacts of previous month. The forth and sixth columns represent p-value of the statistics in the third and fifth columns. The last column is the degree of freedom for each test.

Table 16: Selected Estimation Results of VAR(5) Model

	CDS_t Variable	Estimate	Prob$>|T|$	YSP_t Variable	Estimate	Prob$>|T|$
Argentina	const	0.16968	0.3117	ysp(t-1)	1.12934	0.0001
	cds(t-1)	0.99048	0.0001	ysp(t-2)	-0.33394	0.0001
	ysp(t-1)	0.16143	0.0001	ysp(t-3)	0.1846	0.0096
	ysp(t-2)	-0.12603	0.0176	ysp(t-5)	0.07951	0.0997
Korea				const	0.02271	0.2604
				cds(t-1)	0.23407	0.0993
				yield(t-1)	0.73449	0.0001
Mexico	cds(t-1)	0.73922	0.0001	ysp(t-1)	1.03378	0.0001
	ysp(t-1)	0.44887	0.0001			
	ysp(t-2)	-0.24631	0.0003			
	cds(t-4)	0.16009	0.0364			
Russia	cds(t-1)	0.96375	0.0001	ysp(t-1)	1.01162	0.0001
	ysp(t-1)	0.23467	0.0001	cds(t-2)	-0.25338	0.013
	cds(t-2)	-0.18471	0.0277			
	ysp(t-4)	0.14479	0.0346			
	yspd(t-5)	-0.14402	0.0072			
Brazil	cds(t-1)	0.65085	0.0001	const	0.09847	0.0181
	ysp(t-1)	0.64202	0.0001	ysp(t-1)	1.05358	0.0001
	cds(t-2)	0.20278	0.0082	ysp(t-5)	-0.15368	0.0301
	ysp(t-2)	-0.39617	0.0001			
	cds(t-5)	0.11637	0.0487			
	ysp(t-5)	-0.19381	0.0062			
Venezuela	cds(t-1)	0.85899	0.0001	const	0.43736	0.0035
	ysp(t-1)	0.35776	0.0002	ysp(t-1)	0.89872	0.0001
	ysp(t-2)	-0.5015	0.0001			
	cds(t-5)	0.15037	0.0232			

YSP_t represents the value of yield spreads at time t; $ysp(t-j)$ is the j^{th} lag of yield spreads, with $cds(t-j)$ the j^{th} lag of CDS rates. The third and sixth columns contains values of estimates, with corresponding probability values of t statistics in the forth and seventh columns.

Table 17: Estimation Results of VAR(2)Model

	CDS	Rates Estimate	Prob> $\|t\|$	Yield	Spreads Estimate	Prob> $\|t\|$
Argentina	1	0.17947	0.2792	1	0.19417	0.379
	cds(t-1)	0.99473	0.0001	cds(t-1)	0.00516	0.9313
	ysp(t-1)	0.16853	0.0001	ysp(t-1)	1.10756	0.0001
	cds(t-2)	-0.00528	0.9069	cds(t-2)	0.03648	0.5436
	ysp(t-2)	-0.15724	0.0001	ysp(t-2)	-0.15394	0.001
Korea	1	0.00466	0.6058	1	0.0376	0.0645
	cds(t-1)	1.00077	0.0001	cds(t-1)	0.21569	0.1347
	ysp(t-1)	0.02194	0.4379	ysp(t-1)	0.78636	0.0001
	cds(t-2)	-0.0228	0.7248	cds(t-2)	-0.03799	0.7938
	ysp(t-2)	-0.01332	0.6275	ysp(t-2)	0.08225	0.1826
Mexico	1	0.02216	0.2887	1	0.04673	0.0686
	cds(t-1)	0.80569	0.0001	cds(t-1)	-0.00628	0.9285
	ysp(t-1)	0.4154	0.0001	ysp(t-1)	1.03243	0.0001
	cds(t-2)	0.12117	0.0301	cds(t-2)	-0.03159	0.6437
	ysp(t-2)	-0.35873	0.0001	ysp(t-2)	-0.01728	0.7829
Russia	1	0.07393	0.024	1	0.03926	0.3218
	cds(t-1)	0.97031	0.0001	cds(t-1)	0.10983	0.1355
	ysp(t-1)	0.2379	0.0001	ysp(t-1)	1.0289	0.0001
	cds(t-2)	-0.09311	0.1099	cds(t-2)	-0.15252	0.031
	ysp(t-2)	-0.1292	0.0145	ysp(t-2)	0.00572	0.9287
Brazil	1	0.03281	0.4248	1	0.08083	0.0485
	cds(t-1)	0.7434	0.0001	cds(t-1)	0.09483	0.101
	ysp(t-1)	0.58626	0.0001	ysp(t-1)	1.02435	0.0001
	cds(t-2)	0.21628	0.0002	cds(t-2)	-0.04014	0.4794
	ysp(t-2)	-0.54643	0.0001	ysp(t-2)	-0.09349	0.1366
Venezuela	1	0.24689	0.2226	1	0.4329	0.0026
	cds(t-1)	0.83039	0.0001	cds(t-1)	0.05094	0.2605
	ysp(t-1)	0.39522	0.0001	ysp(t-1)	0.92832	0.0001
	cds(t-2)	0.1591	0.0141	cds(t-2)	-0.0041	0.9282
	ysp(t-2)	-0.40809	0.0001	ysp(t-2)	-0.02159	0.742

Table 18: Comparison of VAR(5) and VAR(2) Models

		AICC	HQC	adjustR^2_{cds}	adjust R^2_{ysp}	data
Argentina	VAR(5)	4.603681	4.676033	0.996121	0.990813	491
	VAR(2)	4.585487	4.618738	0.996068	0.990623	
Korea	VAR(5)	-11.9135	-11.7998	0.97755	0.956035	265
	VAR(2)	-11.9091	-11.856	0.97756	0.954206	
Mexico	VAR(5)	-10.6159	-10.5234	0.975199	0.974273	355
	VAR(2)	-10.6351	-10.5923	0.974411	0.974512	
Russia	VAR(5)	-7.38836	-7.30359	0.994358	0.993435	399
	VAR(2)	-7.40265	-7.36354	0.994242	0.993434	
Brazil	VAR(5)	-7.20924	-7.13561	0.989991	0.986519	480
	VAR(2)	-7.22331	-7.18946	0.989815	0.986386	
Venezuela	VAR(5)	-4.27576	-4.17192	0.971658	0.95997	302
	VAR(2)	-4.33281	-4.28453	0.971724	0.95936	

Table 19: Estimation Results of VAR(2)-ARCH(1) Model

	CDS Rates			yield spreads		
	Variable	Estimate	Pr> $\|t\|$	Variable	Estimate	Pr> $\|t\|$
Argentina	cons	0.43659	0.0001	cons	0.16417	0.1028
	cds(t-1)	1.17826	0.0001	cds(t-1)	0.21775	0.0184
	ysp(t-1)	0.06083	0.0084	ysp(t-1)	0.98615	0.0001
	cds(t-2)	0.66654	0.0001	cds(t-2)	0.25424	0.0092
	ysp(t-2)	-1.04363	0.0001	ysp(t-2)	-0.53456	0.0001
Korea	cons	0.01785	0.0652	cons	0.05885	0.0148
	cds(t-1)	1.0286	0.0001	cds(t-1)	0.18419	0.3979
	ysp(t-1)	-0.02054	0.5964	ysp(t-1)	0.82274	0.0001
	cds(t-2)	-0.04197	0.6063	cds(t-2)	-0.10361	0.6178
	ysp(t-2)	0.0139	0.6903	ysp(t-2)	0.08691	0.2455
Mexico	cons	0.0544	0.0042	cons	0.08126	0.0089
	cds(t-1)	0.7894	0.0001	cds(t-1)	-0.07348	0.4073
	ysp(t-1)	0.41271	0.0001	ysp(t-1)	1.05856	0.0001
	cds(t-2)	0.14209	0.0188	cds(t-2)	0.04372	0.6132
	ysp(t-2)	-0.37345	0.0001	ysp(t-2)	-0.06362	0.4119
Russia	cons	0.16719	0.0083	cons	0.17531	0.0228
	cds(t-1)	1.13794	0.0001	cds(t-1)	-0.05033	0.7296
	ysp(t-1)	0.02705	0.7942	ysp(t-1)	1.10619	0.0001
	cds(t-2)	-0.28123	0.012	cds(t-2)	-0.04398	0.7528
	ysp(t-2)	0.09107	0.4022	ysp(t-2)	-0.03746	0.7871
Brazil	cons	0.09972	0.0989	cons	0.14447	0.0073
	cds(t-1)	0.66215	0.0001	cds(t-1)	0.00425	0.9534
	ysp(t-1)	0.49088	0.0001	ysp(t-1)	0.9395	0.0001
	cds(t-2)	0.29824	0.0001	cds(t-2)	0.05507	0.4392
	ysp(t-2)	-0.46598	0.0001	ysp(t-2)	-0.02633	0.7518
Venezuela	cons	0.22509	0.0153	cons	0.36189	0.0036
	cds(t-1)	0.88414	0.0001	cds(t-1)	0.07822	0.0813
	ysp(t-1)	0.24731	0.0001	ysp(t-1)	0.89757	0.0001
	cds(t-2)	0.08024	0.0255	cds(t-2)	-0.03971	0.3755
	ysp(t-2)	-0.23805	0.0001	ysp(t-2)	0.02391	0.6937

Table 20: Bivariate ARCH Estimates in VAR(2)-ARCH(1) Model

	Parameter	Estimate	S.D.	t Value	Pr> $\|t\|$
Argentina	c_1	3.27373	0.04182	78.29	0.0001
	c_2	6.33739	0.21495	29.48	0.0001
	c_3	0.41825	0.12199	3.43	0.0007
	a_{11}	1.9859	0.05254	37.8	0.0001
	a_{21}	-0.31208	0.06497	-4.8	0.0001
	a_{12}	0.65688	0.11238	5.84	0.0001
	a_{22}	0.11443	0.10524	1.09	0.2775
Korea	c_1	0.03929	0.04949	0.79	0.428
	c_2	0.07384	0.00667	11.07	0.0001
	c_3	0.07338	0.06971	1.05	0.2935
	a_{11}	0.5616	0.31103	1.81	0.0721
	a_{21}	0.0849	0.04279	1.98	0.0483
	a_{12}	-0.61757	0.31844	-1.94	0.0535
	a_{22}	-0.16697	0.10362	-1.61	0.1083
Mexico	c_1	0.06684	0.04416	1.51	0.131
	c_2	0.07767	0.00517	15.01	0.0001
	c_3	0.07108	0.04978	1.43	0.1542
	a_{11}	0.57844	0.17651	3.28	0.0012
	a_{21}	0.0205	0.07012	0.29	0.7701
	a_{12}	-0.11164	0.1339	-0.83	0.405
	a_{22}	0.15187	0.09168	1.66	0.0985

The three univariate representations of bivariate ARCH(1) model are written as:

$$h_{11,t} = c_1 + a_{11}^2\epsilon_{1,t-1}^2 + 2a_{11}a_{21}\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{21}^2\epsilon_{2,t-1}^2,$$

$$h_{12,t} = c_2 + a_{11}a_{12}\epsilon_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{21}a_{22}\epsilon_{2,t-1}^2,$$

$$h_{22,t} = c_3 + a_{12}^2\epsilon_{1,t-1}^2 + 2a_{12}a_{22}\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{22}^2\epsilon_{2,t-1}^2.$$

$h_{11,t}$, $h_{12,t}$, and $h_{22,t}$ are calculated given parameter estimates from above table. $h_{11,t}$ and $h_{22,t}$ represent the variances of CDS rates and yield spreads at time t respectively, $h_{12,t}$ is the covariance of CDS rates and yield spreads at time t. Estimatesv́alues are listed in column 2, where the corresponding standard errors, t values and probability values of the t values in column 3, 4 and 5. Nonlinear maximization is used, and convergence of each regression is required. When the estimate of standard error is very close to zero, the t value and p value will be undefined and shown as 'N/A'.

Table 21: Bivariate ARCH Estimates in VAR(2)-ARCH(1) Model Contd.

	Parameter	Estimate	S.D.	t Value	Pr> $\|t\|$
Russia	c_1	0.30898	0.03572	8.65	0.0001
	c_2	0.34636	0.01408	24.6	0.0001
	c_3	0.13185	0.05886	2.24	0.0256
	a_{11}	0.49155	0.3046	1.61	0.1074
	a_{21}	-0.26091	0.12205	-2.14	0.0331
	a_{12}	-0.39313	0.17632	-2.23	0.0263
	a_{22}	0.43624	0.14667	2.97	0.0031
Brazil	c_1	0.32076	0.03246	9.88	0.0001
	c_2	0.23136	0.00945	24.48	0.0001
	c_3	0.11525	0.04918	2.34	0.0195
	a_{11}	0	40.02207	0	1
	a_{21}	0.0165	0.10285	0.16	0.8726
	a_{12}	-0.42397	0.08316	-5.1	0.0001
	a_{22}	0.07288	0.10312	0.71	0.4801
Venezuela	c_1	0.20675	0.065	3.18	0.0016
	c_2	-0.03417	0.02387	-1.43	0.1534
	c_3	0.24039	0.06063	3.96	0.0001
	a_{11}	1.43765	0.08042	17.88	0.0001
	a_{21}	-0.31456	0.05576	-5.64	0.0001
	a_{12}	0.64894	0.0898	7.23	0.0001
	a_{22}	-0.17557	0.0568	-3.09	0.0022

Table 22: Argentina Pre-Default Sample

	ARCH	ARCH-X	AR-ARCH	AR-ARCH-X
CONS	-3.83964	-3.10328	-10.7025	-10.8719
	(-7.65461)	(-8.66152)	(-32.1121)	(-21.1569)
BSP(t-1)			0.446317	0.430637
			(29.04662)	(23.68385)
BSP(t-2)			0.232156	0.221391
			(18.50211)	(12.41879)
RATE	-1.337708	-1.39388	-0.339732	-0.44099
	(-28.9771)	(-21.8127)	(-8.82693)	(-11.8325)
LIQ	5.251395	5.228378	3.079737	2.577179
	(13.10692)	(11.82388)	(12.45269)	(9.723324)
SLOPE	-0.197146	-0.27971	0.034031	-0.01342
	(-3.67022)	(-3.59583)	(0.79119)	(-0.27002)
YR10	-2.706155	-2.63439	-2.426922	-2.45282
	(-25.493)	(-24.7688)	(-52.4553)	(-31.1298)
$YR10^2$	9.796264	9.468309	10.12896	10.6854
	(43.35867)	(40.68505)	(61.47944)	(38.01775)
DUMB3160	0.086576	0.122713	0.043568	-0.0015
	(3.102148)	(4.02889)	(2.428915)	(-0.0724)
DUMB0130	-0.441941	-0.38191	-0.073905	-0.12682
	(-12.6274)	(-9.1711)	(-3.59719)	(-4.73114)
DUMA0010	0.092559	0.136079	0.080457	0.03848
	(3.072807)	(1.987432)	(2.068325)	(1.284717)
DUMA1130	-0.045089	-0.09942	-0.054363	-0.09857
	(-1.34635)	(-2.20338)	(-2.36809)	(-4.38111)
cons	0.089686	0.983501	0.106826	0.955636
	(4.668048)	(4.971964)	(4.145232)	(3.815909)
$\epsilon(t-1)^2$	2.510071	1.710528	2.642133	1.944979
	(4.651782)	(3.931201)	(3.721384)	(3.575992)
LIQ		-0.96303		-0.93931
		(-4.80705)		(-3.74403)
ν	0.743368	0.830843	0.627977	0.700177
	(16.05761)	(15.20421)	(12.21932)	(11.29372)
Adjusted R^2	0.439264	0.444809	0.601156	0.601066
AIC	1.822979	1.766834	1.455742	1.377343
Log Likelihood	-308.7558	-297.846	-240.4828	-225.724

The first part of each table contains estimates in the main equation; the second part has estimates in variance equation, where the GED distribution parameter ν is also reported; the model selection criteria are in the last part.(To be continued at the next page)

Table 23: Korea

	ARCH	ARCH-X	AR-ARCH	AR-ARCH-X
CONS	35.4032	35.46375	10.69913	10.64792
	(89.45647)	(72.83535)	(56.38381)	(3.216088)
BSP(t-1)			0.602029	0.643882
			(12.26186)	(12.6787)
BSP(t-2)			0.092937	0.05122
			(2.052503)	(1.100218)
RATE	-0.28461	-0.31207	-0.05272	-0.04494
	(-10.1052)	(-10.1146)	(-2.08866)	(-1.52575)
LIQ	0.61966	0.648927	0.411919	0.410846
	(13.23047)	(16.28281)	(5.376837)	(5.203843)
SLOPE	-0.14672	-0.13121	-0.06655	-0.06896
	(-6.16525)	(-5.44257)	(-4.48943)	(-4.3024)
YR10	5.915817	5.915808	1.887941	1.881238
	(85.40072)	(67.3393)	(151.2699)	(3.19353)
$YR10^2$	-27.876	-27.8389	-8.79948	-8.78304
	(-94.2775)	(-73.5996)	(-296.911)	(-3.15046)
DUMB3160	-0.03619	-0.04327	0.009892	0.011965
	(-2.33834)	(-2.81795)	(1.058918)	(1.207451)
DUMB0130	-0.07421	-0.07572	0.001749	0.001311
	(-5.87081)	(-6.21046)	(0.192287)	(0.131642)
DUMA0010	-0.00886	0.0044	0.000365	-0.0018
	(-0.3142)	(0.154942)	(0.024578)	(-0.11934)
DUMA1130	0.009089	0.02819	0.001804	-0.00133
	(0.533753)	(1.505195)	(0.170443)	(-0.12372)
cons	0.002702	0.002905	0.003826	-0.00124
	(4.949924)	(0.724235)	(5.297585)	(-0.21954)
$\epsilon(t-1)^2$	0.805608	0.852921	0.321421	0.292588
	(5.333957)	(5.665806)	(1.651041)	(1.593541)
LIQ		-0.00058		0.008846
		(-0.08912)		(0.891196)
ν	2.008507	2.102334	0.930624	0.956085
	(6.64889)	(6.594033)	(8.301506)	(8.238116)
Adjusted R^2	0.68455	0.684387	0.84565	0.845748
AIC	-2.03584	-2.02839	-2.54123	-2.53625
Log Likelihood	282.7481	282.762	349.1719	349.5171

BSP(t-1) is the first lag of basis spreads; where the BSP(t-2) is the second lag. YR10 represents the level of yield curve, Slope refers to the change of yield curve. LIQ ratio measures liquidity. The values in brackets are t statistics of corresponding estimates.

Table 24: Mexico

	ARCH	ARCH-X	AR-ARCH	AR-ARCH-X
CONS	-0.11204	0.33383	0.173418	0.092796
	(-0.69805)	(1.867575)	(0.628015)	(0.205542)
BSP(t-1)			0.599111	0.590282
			(11.03261)	(11.03343)
BSP(t-2)			0.174585	0.174762
			(3.510433)	(3.589367)
RATE	0.05551	-0.02313	0.00296	0.012315
	(2.425531)	(-1.05037)	(0.17667)	(0.77219)
LIQ	-0.01569	0.004983	-0.29268	-0.2552
	(-0.13429)	(0.027582)	(-1.99531)	(-1.61533)
SLOPE	-0.4479	-0.45677	-0.06795	-0.08496
	(-26.5644)	(-22.114)	(-3.8298)	(-4.88442)
YR10	-0.26489	-0.3091	-0.05216	-0.08463
	(-6.35182)	(-9.04319)	(-0.93803)	(-0.99147)
$YR10^2$	0.96606	1.094108	0.188283	0.278124
	(8.920536)	(11.16607)	(0.824498)	(0.726448)
DUMB3160	-0.0216	-0.01	-0.00138	0.008017
	(-1.09349)	(-0.55602)	(-0.08112)	(0.494555)
DUMB0130	0.156236	0.156722	0.025892	0.033007
	(7.468019)	(7.417447)	(1.564273)	(2.132645)
DUMA0010	0.088558	0.141825	0.03404	0.034339
	(2.726441)	(3.871157)	(1.124192)	(1.269376)
DUMA1130	-0.00945	0.042568	-0.01108	-0.01169
	(-0.37349)	(1.70477)	(-0.60052)	(-0.69369)
cons	0.003793	0.011306	0.004235	0.010359
	(6.614216)	(3.227365)	(7.224167)	(1.572083)
$\epsilon(t-1)^2$	0.869617	0.742421	0.240188	0.25262
	(5.285049)	(4.318628)	(1.757352)	(1.836378)
LIQ		-0.01108		-0.01051
		(-2.05408)		(-0.95571)
ν	1.638668	1.532589	1.263997	1.212364
	(9.460772)	(13.56231)	(8.554265)	(8.655584)
Adjusted R^2	0.750291	0.743103	0.891531	0.890428
AIC	-1.82988	-1.77447	-2.38192	-2.38215
Log Likelihood	337.8029	328.9691	435.4087	436.4493

Table 25: Russia

	ARCH	ARCH-X	AR-ARCH	AR-ARCH-X
CONS	57.80854	63.39098	8.517497	8.382185
	(136.8853)	(175.4906)	(1.75436)	(14.82534)
BSP(t-1)			0.87113	0.85836
			(21.12021)	(19.90918)
BSP(t-2)			0.022581	0.036896
			(0.565576)	(0.876436)
RATE	-1.04473	2.083492	-0.08159	-0.00929
	(-14.4216)	(12.65753)	(-1.94848)	(-0.11832)
LIQ	1.623343	-1.30231	0.019799	-0.07548
	(12.32312)	(-14.8915)	(0.209441)	(-1.75068)
SLOPE	-0.02928	0.015664	0.011724	0.018287
	(-1.27721)	(0.623685)	(0.552235)	(0.985961)
YR10	8.990298	9.722619	1.42092	1.420472
	(164.0338)	(227.5173)	(1.68144)	(15.6768)
$YR10^2$	-43.8373	-47.523	-6.80419	-6.75604
	(-190.948)	(-606.073)	(-1.68573)	(-15.7763)
DUMB3160	-0.50986	-0.5843	-0.04568	-0.04416
	(-15.4987)	(-16.1463)	(-2.15536)	(-2.1053)
DUMB0130	-0.58459	-0.69868	-0.04328	-0.03997
	(-19.9331)	(-20.4594)	(-1.82949)	(-2.16035)
DUMA0010	0.088667	0.132128	0.036918	0.04061
	(1.744913)	(2.807597)	(1.608728)	(1.651794)
DUMA1130	0.362261	0.372127	0.028644	0.027629
	(12.94803)	(13.29575)	(1.690938)	(1.518678)
cons	0.009641	0.026593	0.019484	0.040215
	(5.568437)	(7.112617)	(7.351588)	(6.101404)
$\epsilon(t-1)^2$	1.135111	1.058102	0.304321	0.20091
	(7.780757)	(8.065652)	(1.993412)	(1.625553)
LIQ		-0.02735		-0.03643
		(-6.4934)		(-4.34574)
ν	2.108254	2.31426	0.908	0.968881
	(11.1089)	(10.85569)	(12.12059)	(11.26501)
Adjusted R^2	0.505281	0.496129	0.85571	0.855933
AIC	-0.11744	-0.13449	-0.98006	-1.01644
Log Likelihood	37.01643	41.50399	214.4427	222.8456

Table 26: Brazil

	ARCH	ARCH-X	AR-ARCH	AR-ARCH-X
CONS	-1.98917	-1.80695	-0.18913	-0.21838
	(-2.73501)	(-2.49138)	(-0.04888)	(-0.04495)
BSP(t-1)			0.592743	0.584078
			(13.33783)	(12.99329)
BSP(t-2)			0.236165	0.24593
			(5.620257)	(5.732093)
RATE	0.013161	-0.00337	-0.01498	-0.01437
	(0.251672)	(-0.07277)	(-0.4236)	(-0.44031)
LIQ	1.419598	1.308463	0.148074	0.17878
	(4.764668)	(4.624003)	(0.445161)	(0.478932)
SLOPE	-0.46543	-0.44969	-0.0471	-0.04988
	(-16.8573)	(-15.8248)	(-2.19869)	(-2.21034)
YR10	-0.28231	-0.27241	0.028612	0.02318
	(-2.34587)	(-2.11666)	(0.044349)	(0.028677)
$YR10^2$	1.018691	0.986299	-0.02168	-0.00612
	(2.065665)	(1.875883)	(-0.00708)	(-0.00159)
DUMB3160	-0.01295	0.0271	0.002478	-0.00403
	(-0.1757)	(0.512945)	(0.047417)	(-0.10474)
DUMB0130	-0.16386	-0.14118	-0.02636	-0.03367
	(-3.69483)	(-4.11105)	(-0.75236)	(-1.12449)
DUMA0010	-0.15279	-0.14245	-0.03197	-0.04223
	(-2.29449)	(-2.66821)	(-0.71806)	(-1.04799)
DUMA1130	-0.03351	-0.02783	0.017369	0.010194
	(-0.59925)	(-0.52355)	(0.518703)	(0.320119)
cons	0.018889	0.084103	0.017862	0.070997
	(9.934548)	(4.044651)	(9.457076)	(3.776652)
$\epsilon(t-1)^2$	0.619737	0.604983	0.232923	0.209538
	(5.259909)	(5.310131)	(2.389681)	(2.201007)
LIQ		-0.07472		-0.06076
		(-3.22587)		(-2.97485)
ν	2.356566	2.510023	1.607332	1.656964
	(13.03393)	(12.14263)	(9.259396)	(9.415078)
Adjusted R^2	0.62361	0.623437	0.859106	0.858849
AIC	-0.32168	-0.3312	-0.9185	-0.92667
Log Likelihood	90.20343	93.48714	234.5205	237.473

Table 27: Venezuela

	ARCH	ARCH-X	AR-ARCH	AR-ARCH-X
CONS	-0.10911	-0.63527	-0.14262	-0.16002
	(-0.08784)	(-0.48856)	(-1.04306)	(-0.97488)
BSP(t-1)			0.883417	0.908113
			(18.83162)	(21.2529)
BSP(t-2)			0.094315	0.088212
			(2.028834)	(2.07166)
LIQ	-0.58522	-0.11492	0.276172	0.330342
	(-0.77136)	(-0.12346)	(1.861352)	(1.927777)
SLOPE	-2.91795	-3.0315	-0.09704	-0.03626
	(-28.8924)	(-21.3145)	(-1.81136)	(-0.72284)
YR10	-2.23765	-2.58812	-0.00045	0.072853
	(-6.79034)	(-7.31082)	(-0.00544)	(0.970367)
$YR10^2$	7.668508	8.651771	0.040144	-0.18595
	(6.619608)	(7.167797)	(0.171333)	(-0.83983)
cons	0.13919	-0.50364	0.066665	-0.04735
	(6.663696)	(-3.77265)	(4.361637)	(-0.2856)
$\epsilon(t-1)^2$	0.723668	0.72991	0.752514	0.702028
	(3.517925)	(4.096756)	(3.193123)	(2.995515)
LIQ		0.88149		0.162384
		(4.327202)		(0.687921)
ν	2.226638	2.41783	0.821696	0.796434
	(9.651191)	(8.674626)	(9.71347)	(10.06827)
Adjusted R^2	0.636355	0.655296	0.912663	0.910835
AIC	1.919824	1.90948	0.441678	0.449082
Log Likelihood	-281.893	-279.332	-56.2517	-56.3624

Table 28: Common Factor Tests

Hypotheses	D.F.	χ^2	Pr $> \chi^2$
H_0: No common factors H_1: At least one common factor	21	131.5731	<.0001
H_0: 1 Factor is sufficient H_1: More factors are needed	14	18.4438	0.1873

Table 29: Common Factor Analysis Summary

TYPE	Korea	Mexico	Russia	Brazil	Venezuela
MEAN	-0.00068449	-0.001464381	0.010349	-0.020171818	0.034014
STD	0.055031818	0.060456378	0.075705	0.144924293	0.519677
N0.:	110	110	110	110	110
COMMUNALITY	0.207334576	0.46134308	0.416063	0.244292176	0.044913
EIGENVALUE	0.42298529	0.141121697	0.022429	-0.183229782	-0.33778
FACTOR COEF.	0.455340066	0.679222409	0.645029	0.49425922	0.211927
CORRELATION					
Korea	1	0.332912141	0.261598	0.090815667	0.057147
Mexico	0.332912141	1	0.436046	0.370061945	0.112517
Russia	0.261598179	0.436046106	1	0.346944729	0.164252
Brazil	0.090815667	0.370061945	0.346945	1	0.328056
Venezuela	0.057146618	0.11251679	0.164252	0.328056279	1

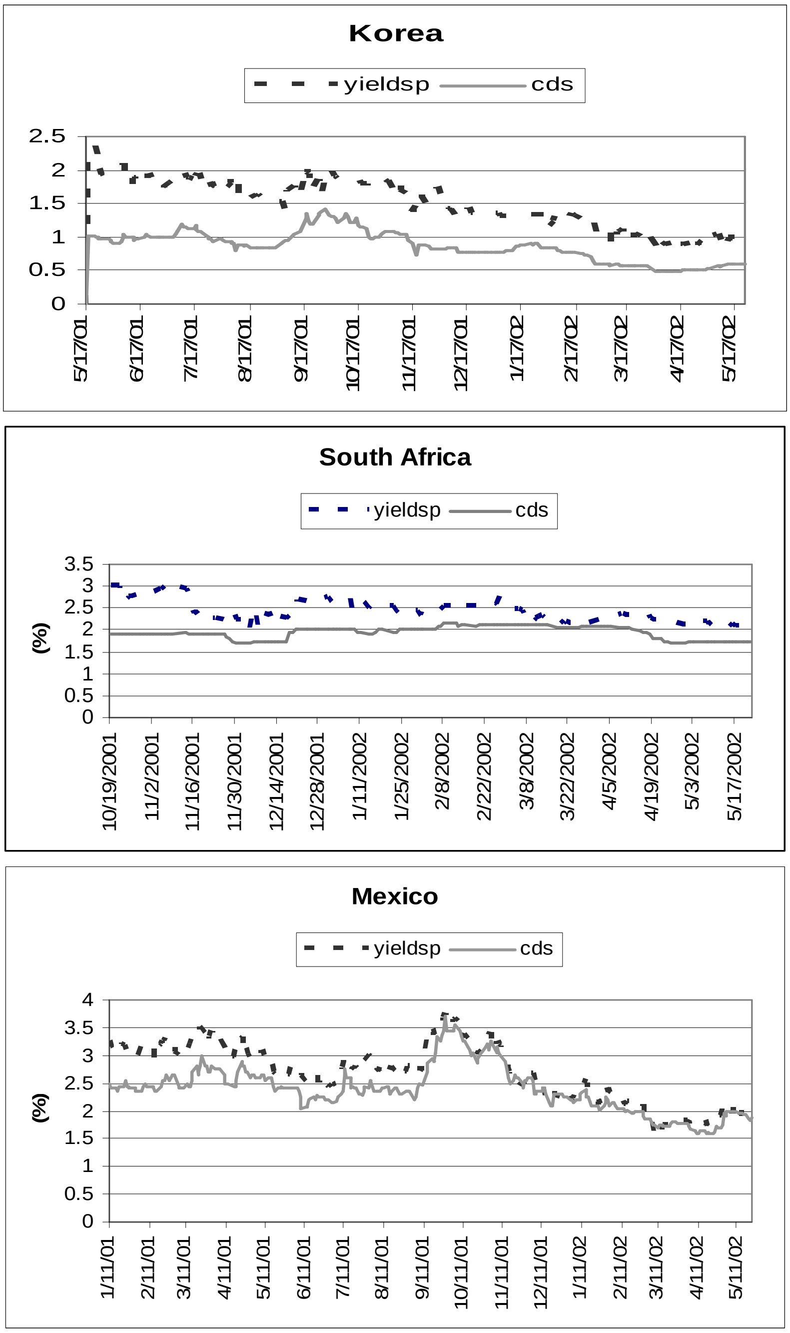

Figure 2: Investment Grade Sovereigns

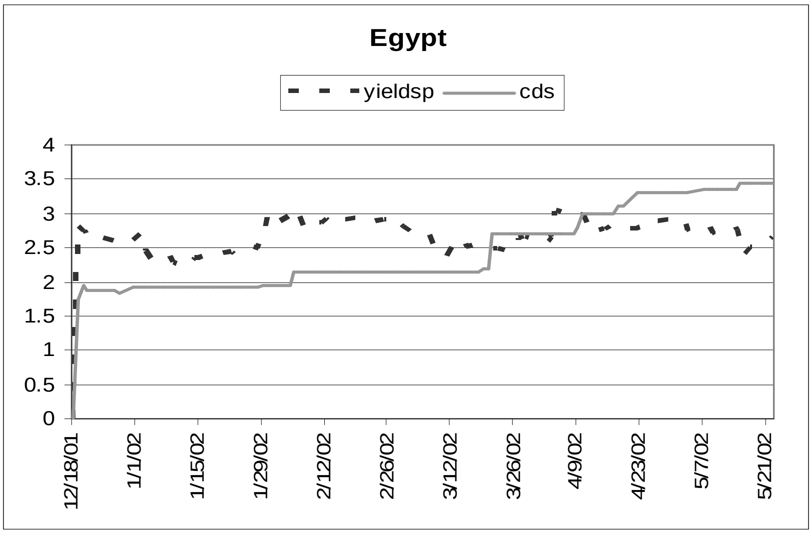

Figure 3: speculative grade Sovereigns

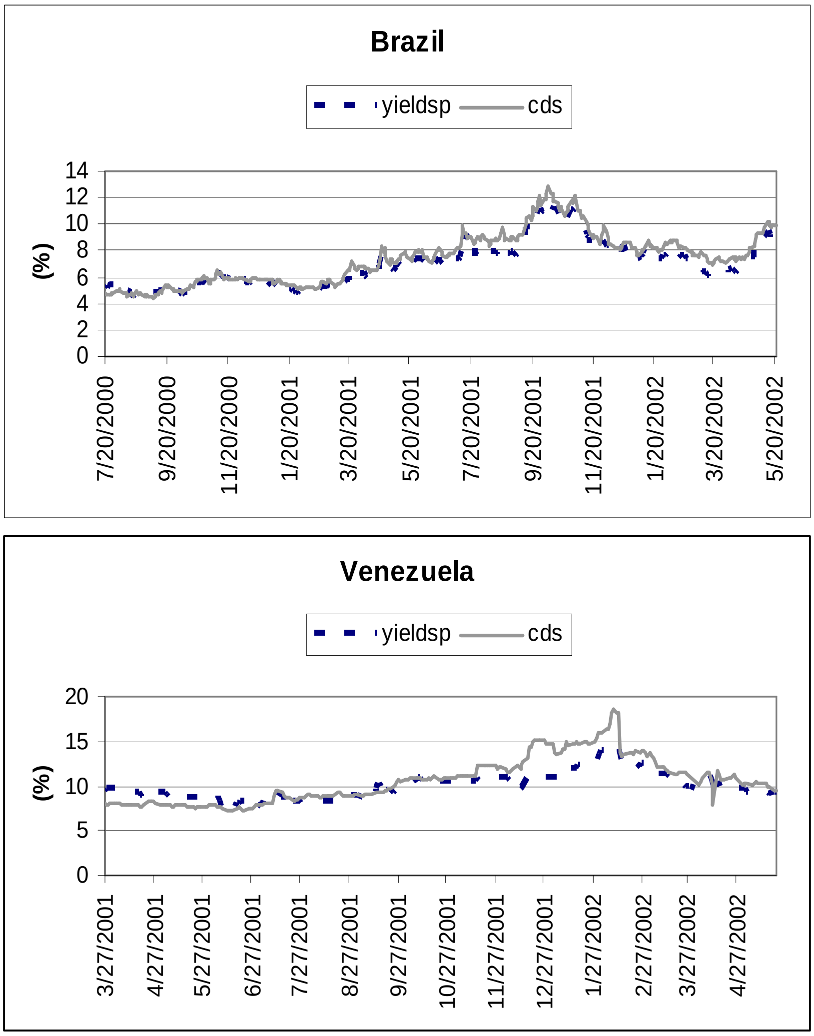

Figure 4: speculative grade Sovereigns

Figure 5: speculative grade Sovereigns

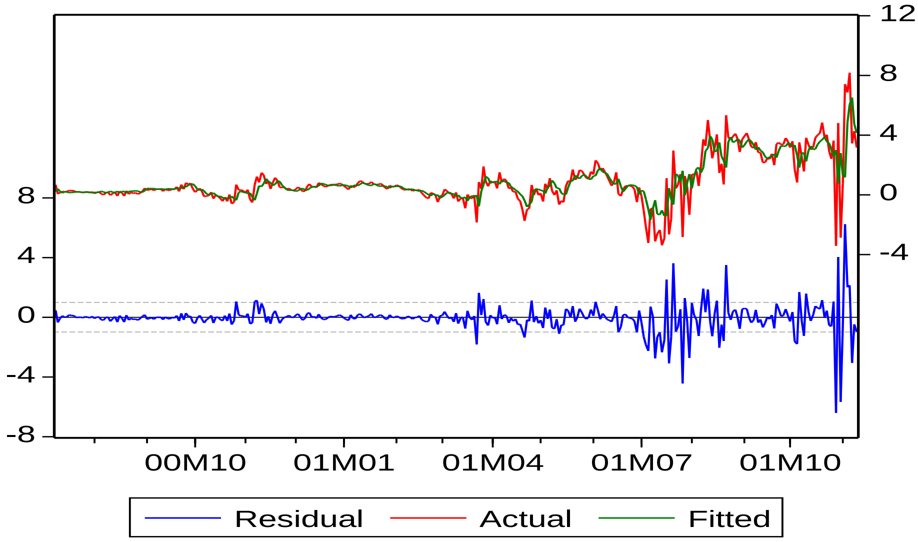

Figure 6: Argentina Subsample Fit

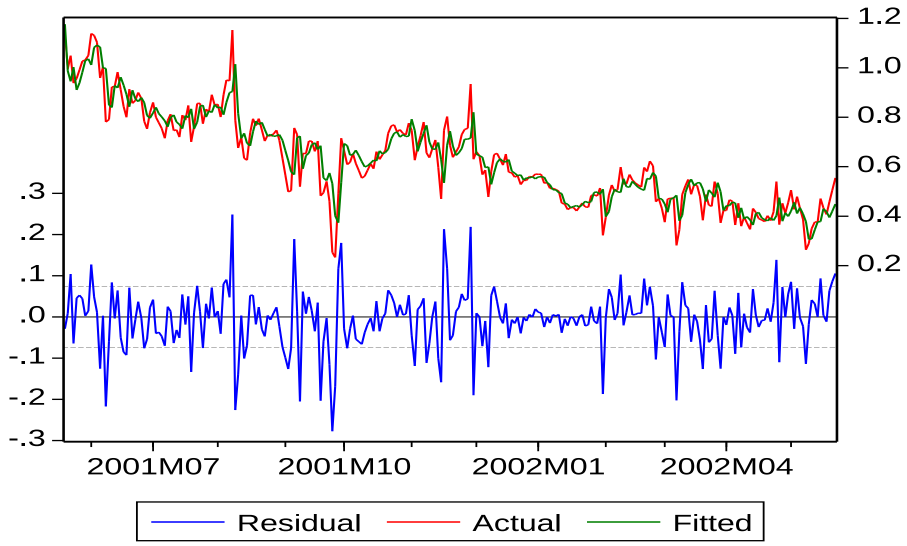

Figure 7: Korea Fit

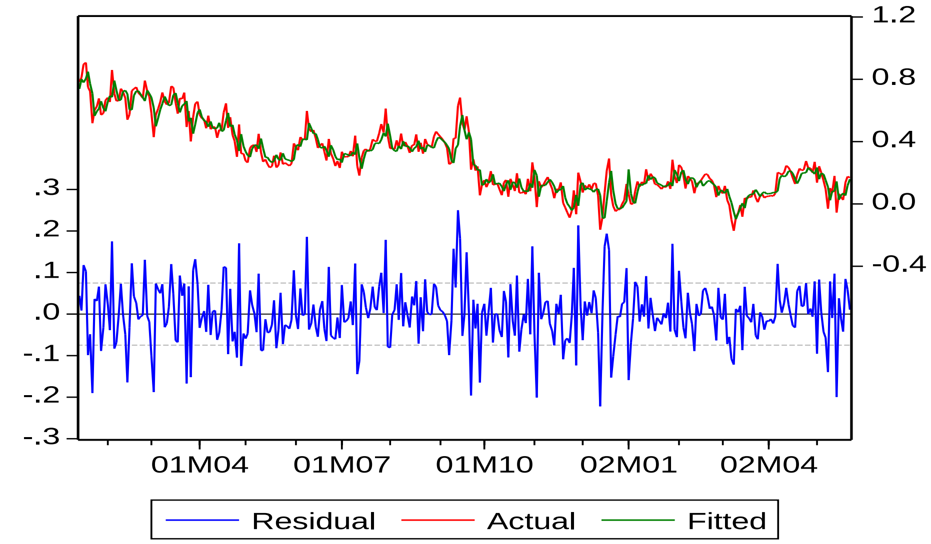

Figure 8: Mexico Fit

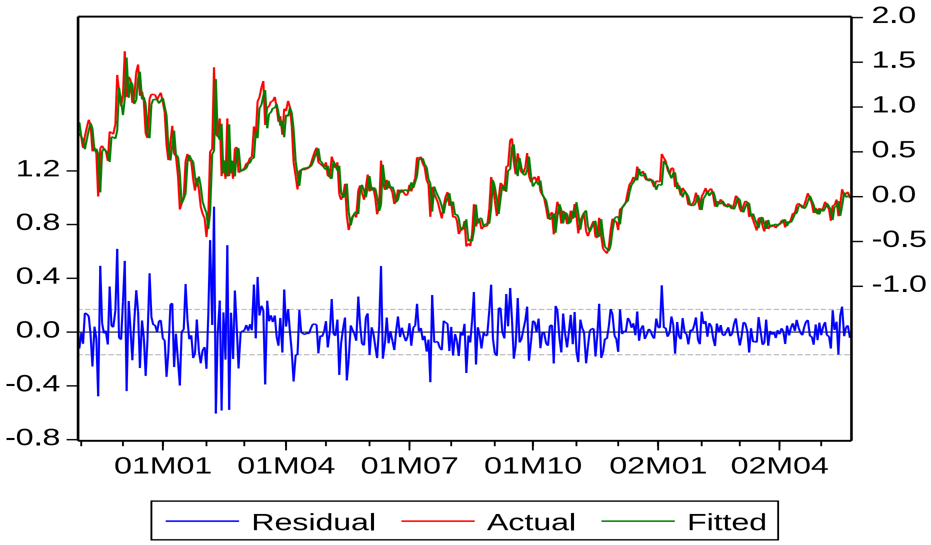

Figure 9: Russia Fit

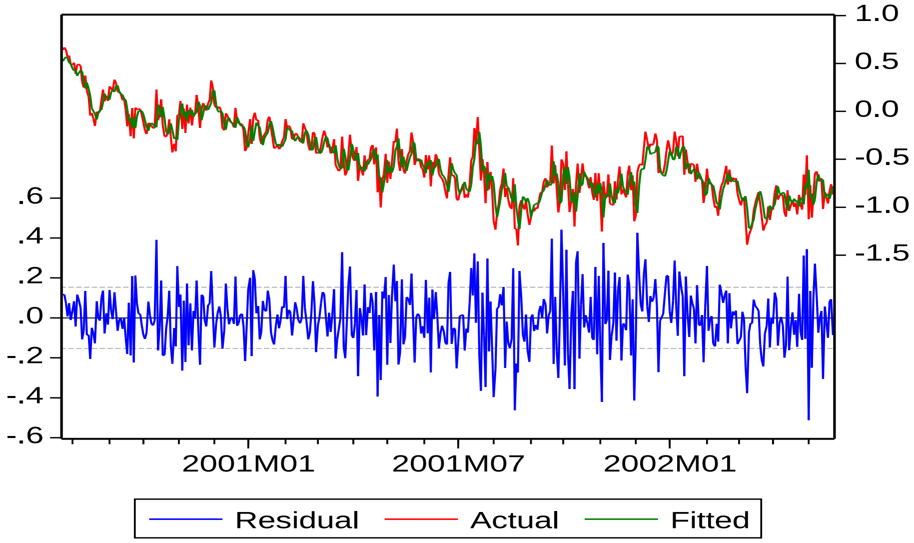

Figure 10: Brazil Fit

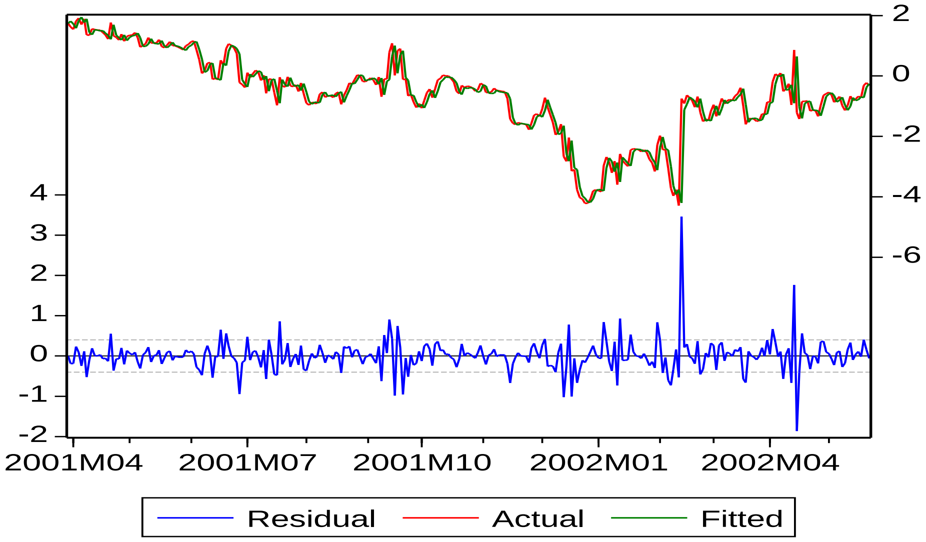

Figure 11: Venezuela Fit

Bibliography

[1] Jeffery D Amato and Eli M Remolona, 2003, *The Credit Spread Puzzle,* Working Paper.

[2] Avramov, Doron, Gergana Jostova, and Alexander Philipov, 2004, *Corporate Credit Risk Changes: Common Factors and Firm-Level Fundamentals,* Working paper, Unversity of Maryland; George Washington University; Fannie Mae.

[3] Jonathan Batten, Thomas Fetherston, Pongsak Hoontrakul, 2004, *Factors Affecting the Yields of Emerging Market Issuers in International Bond Markets: Evidence from the Asia Pacific Region,* Working Paper.

[4] Collin-Dufresne, P., R. S. Goldstein, and J. S. Martin, 2000, *The Determinants of Credit Spread Changes,* Working Paper.

[5] Kenneth N. Daniels and Malene Shin Jensen, 2004, *The Effect of Credit Ratings on Credit Default Swap Spreads and Credit Spreads, University of Aarhus* Working Paper.

[6] Duffie, Darrell, and Kenneth J. Singleton, Credit Risk, 2004.

[7] Duffie, Darrell, Lasse H. Pedersen, and Kenneth J. Singleton, 2003, *Modeling Sovereign Yield Spreads: A Case Study of Russian Debt,* Journal of Finance.

[8] Jan Ericsson, Kris Jacobs, and Rodolfo Oviedo-Helfenberger, 2004, *The Determinants of Credit Default Swap Premia,* Working Paper, McGill University.

[9] Gonzalez-Rivera, G. and Racine, J. S.,1995 , *Maximum Likelihood Estimation and Testing Strategies in GARCH Models,* University of California, Riverside, Working Paper.,

[10] Gruber, Agrawal, and Mann, 2001, *Explaining the Rate Spread on Corporate Bonds,* Journal of Finance, 56(1), 247-277.

[11] Houweling, Patrick, and Ton Vorst, 2003, *Pricing Default Swaps: Empirical Evidence,* Journal of International Money and Finance, Forthcoming.

[12] Hull, John, and Alan White, 2000, *Valuing Credit Default Swaps: No Counterparty Default Risk,* Journal of Derivatives, Vol.8, pp.29 40.

[13] Hull, John, Mirela Predescu, and Alan White, 2004, *The Relationship BetIen Credit Default Swap Spreads, Bond Yields, And Credit Rating Announcements,* Journal of Banking and Finance, forthcoming.

[14] Iglesias, Emma M. and Phillips, Garry D.A., 2004, *Multivariate ARCH Models: Finite Sample Properties of QML Estimators and an Application to an LM-Type Test,* University of Alicante, Working Paper.

[15] Rodolfo Martell, 2003, *Understanding Common Factors in Domestic and International Bond Spreads,* Working Paper.

[16] Lehnert, Thorsten, and Frederick Neske, 2004, *On the Relationship Between Credit Rating Announcements and Credit Default Swap Spreads for European Reference Entities,* Working paper, Maastricht Unversity.

[17] Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2003, *The Credit Default Swap Markte: Is Credit Protection Priced Correctly?,* Working paper, UCLA.

[18] Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2004, *Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit-Default Swap Market,* Working paper, UCLA.

[19] Marian Micu, Remolona and Wooldridge, 2004, *The price impact of rating announcements: evidence from the credit default swap market,* BIS Quarterly Review.

[20] Ming, H. G., 1998, *The determinants of Emerging Market bond spread: Do economic fundamentals matter?,* Policy Research Working Paper 1899, The World Bank.

[21] Neftci, Salih, Andre Oliveira Santos, and Yinqiu Lu, 2004, *Credit Default Swaps and Financial Crisis Prediction.* Working paper, City University of New York.

[22] Frank Packer and Chamaree Suthiphongchai, 2003, *Sovereign credit default swaps,* BIS Quarterly Review, December.

[23] Michael Westphalen, 2001, *The Determinants of Sovereign Bond Credit Spreads Changes,* Working Paper.

[24] Yan Alice Xie, Chunchi Wu and Jian Shi, 2004, *Do Macroeconomic Variables Matter for the Pricing of Default Risk? Evidence from the Residual Analysis of the Reduced-Form Model Pricing Errors* Working Paper.

[25] Frank X. Zhang, 2003, *What Did the Credit Market Expect of Argentina Default? Evidence from Default Swap Data,* Working paper, Federal Reserve Board.

[26] Haibin Zhu, 2004, *An empirical comparison of credit spreads between the bond market and the credit default swap market,* BIS Working Paper.