ESSAYS ON CREDIT DEFAULT SWAPS

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ABSTRACT

This thesis is structured to research on a financial derivative asset known as a credit default swap (CDS). A CDS is a contract in which the buyer of protection makes a series of payments (often referred to as CDS spreads) to the protection seller and, in exchange, receives a payoff if a default event occurs. A default event can be defined in several ways, including failure to pay, restructuring or rescheduling of debt, credit event repudiation, moratorium and acceleration.

The main motivation of my PhD thesis is to investigate the determinants of the changes of CDS spreads and to model the evolution of spreads. Two widely traded types are corporate and sovereign CDS contracts, the first has as its underlying asset a corporate bond and, hence, hedges against the default risk of a company; the second type hedges against the default risk of a sovereign country. The two contract types have different risk profiles; for example, it is known that liquidity premium with different maturity varies significantly for a corporate CDS but less so for a sovereign CDS because, in contrast with the corporate markets where a majority of the trading volume is concentrated on the 5-year CDS, the sovereign market has a more uniform trading volume across maturities.

In light of the difference, this thesis is divided into four parts. Part A introduces the motivation and research questions of this thesis, followed by literature review on debt valuation, with emphasis on default and liquidity spreads modelling. Part B aims at the role liquidity risk plays in explaining the changes in corporate CDS spreads. Part C models sovereign CDS spreads with macro and latent factors in a no-arbitrage framework. Part D concludes this thesis with a list of limitations and further research direction.

Keywords: credit default swap; credit risk; liquidity risk; regime switching; sovereign risk; spillover; term structure; macroeconomic factors; principal component analysis; Kalman Filter

JEL classification: C13, E42, E44, G12, G01, G12, G15

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Abbreviation List

ADF	Augmented Dickey-Fuller
BPS	Basis points
CAPM	Capital asset pricing model
CBOE	Chicago board options exchange
CDS	Credit default swap
CIR	Cox-Ingersoll-Ross
COCB	Cash-only part of convertible bond
CPI	Consumer price index
ELCB	Equity-like part convertible bond
EWMA	Exponentially weighted moving averaged
GDP	Gross domestic production
LEV	Leverage ratio
Libor-Tbill	Spread between 3-month Libor and 3-month Treasury Bill yield
IPI	Industrial production index
NBER	National bureau of economic research
ODE	Ordinary differential equation
OLS	Ordinary least squares
PCA	Principal component analysis
PCE	Personal consumption expenditure
PPI	Producer price index
RMSE	Root mean square error
SD	Standard deviation
STLFSI	St. Louis federal reserve's financial stress index
VOL	Volatility

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Part A: Introduction and Literature Review on Debt Research

Abstract A

In this chapter I propose the research questions and the motivation of this thesis. In order to find its contributions I then review the current literature on valuation of debt assets considering credit risk, liquidity risk or both. Pros and cons of selected papers are analysed. The purpose of this section is to summarize different pricing models under several assumptions of the dynamics of pricing factors and, therefore, to link the empirical studies in Chapters B and C to the existing literature.

Chapter A1. Introduction

Pioneered by Black and Scholes (1973) and Merton (1974), research on default has grown extensively in the last three decades. Black and Scholes (1973) is undoubtedly one of the most influential papers in the financial economics world, attempting to pricing options and corporate liabilities. Merton (1974) assesses the credit risk of a company by treating the company's equity as a call option on its assets, and the company's credit risk can then be measured by the value of a put option. Since then, researchers have been working hard to improve the modelling on default, to produce more accurate results and to explain default spreads more realistically. For instance, searching the keywords "default risk" in Google scholar returns 284,000 articles since 2005.

Yet much remains to be done, default risk in financial markets has changed dramatically over the last few years, especially since the beginning of the financial crisis in 2007. A report in Moody (2011) shows the average credit loss rate has increased exponentially from 0.17% in 2007 to 3.41% in 2009, the highest in last 20 years. To be specific, I list several major recent credit events as follows (Guillen, 2012):

February 7, 2007: HSBC announces losses linked to US subprime mortgages;
April 3, 2007: New Century Financial, which specializes in sub-prime mortgages, files for Chapter 11 bankruptcy protection and cuts half of its workforce;

June 2007: Two Bear Stearns-run hedge funds with large holdings of subprime mortgages run into large losses and are forced to dump assets;

August 28, 2007: German Sachsen Landesbank faces collapse after investing in the sub-prime market;

September 14, 2007: Depositors withdraw £1bn from Northern Rock in what is the biggest run on a British bank for more than a century;

March 16, 2008: Bear Stearns is bought by J.P. Morgan Chase;

September 7, 2008: Mortgage lenders Fannie Mae and Freddie Mac are rescued by the US government in one of the largest bailouts in US history;

September 15, 2008: Bank of America agrees to a $50 billion rescue package for Merrill Lynch. Lehman files for bankruptcy;

1 April 2009: Unemployment across the Eurozone rose to its highest level.

All the events above indicate the strong impacts of default risk on the financial world, on the other hand, researchers realize a large fraction of the variation in default spreads remains unexplained by existing models (see Huang and Huang, 2002, Ericsson, et al., 2009). Therefore the main objective of this thesis is to extend existing models and to improve our understanding on default risk. It is acknowledged in the literature that CDS (credit default swap) spreads are superior to bond spreads for default research through more accurate data and higher trading frequency. Two widely traded CDS types are corporate and sovereign CDS, the first has as its underlying asset a corporate bond and, hence, hedges against the default risk of a company; the second type hedges against the default risk of a sovereign country. In this thesis I focus on the analysis on CDS contracts by asking the research questions:

- How can existing models explain default spreads using more recent data? The financial crisis has changed the risk profile of the financial market, an examination of models' performance before and after the beginning of financial crisis is therefore necessary.
- Can I find other determinants implied by conventional models of default to explain corporate default spreads more accurately? Specifically, the increasing significance of liquidity risk for the valuation of equity and corporate bond has been investigated (Liu, 2006, Chen et al., 2007), I will aim to examine the role of liquidity for CDS valuation.
- Can I propose an accurate pricing model for sovereign default spreads by incorporating macro and latent factors? There is extensive literature on modelling credit risk by either macro factors (Hilscher and Nosbusch, 2010, Longstaff et al., 2011) or latent factors (Duffie, et al., 2003, Houweling and Vorst, 2005, Pan and Singleton, 2008). I will combine these factors, take the advantages of each approach and compare the performance of my model.

Answering those research questions will allow me to make both empirical and methodological contributions. Before presenting my empirical results and possible gaps this thesis has filled, I review the literature on valuation of debt assets considering credit risk, liquidity risk or both. In Chapter A2 I review the models on interest rate, credit and liquidity spread. Chapter A3 summarizes the methodology commonly applied in default research, and Chapter A4 reviews the popular models for CDS valuation, given the focus of this thesis is on CDS contracts. Finally Chapter A5 concludes this chapter by providing a link to the empirical studies in Chapter B and C.

Chapter A2. Model Review

Bearing in mind to fill the gap of default research, in this section, I summarize influential papers relevant to the pricing of a defaultable corporate bond and some associated derivative asset, such as a convertible bond, bond with embedded options, CDS, with emphasis on credit and liquidity spread modelling.

A2.1 The interest rate model

Let the dynamics of risk-free interest rate be given by the following diffusion process:

$$dr = u(r,t)dt + \varpi(r,t)d\omega$$

where ω is a Wiener process, u and ϖ are the time dependent expected rate of return and volatility of the spot interest rate. In selecting the specific form of interest rate model for valuation, note that Brennan and Schwartz (1980) and Ammann et al. (2008) find a rather small effect of stochastic interest rate models on a convertible bond fair price. Cox et al. (1985), and Mallier and Deakin (2002) choose a general affine model, the Cox-Ingersoll-Ross (CIR), model by assuming the dynamics of interest rate follows a square root process[1]

$$u = a(b - r) \text{ and } \varpi = \sigma_r r^{1/2}$$

This ensures a mean reversion of the interest rate towards the long run value b, with speed of adjustment governed by the strictly positive parameter a; the standard deviation factor $\sigma_r r^{1/2}$ avoids the possibility of negative interest rates

[1] I suppress the time dependence to keep the notation light.

for all nonnegative values of a and b. Duffee (1999), Duffie and Singleton (1997), and Jarrow et al. (2010) use a two-factor affine model for the spot interest rate r,

$$r_t = \alpha + s_{1,t} + s_{2,t}$$

Where α is a constant, and the two state variables $s_{1,t}, s_{2,t}$ represent the slope and level of the interest rate yield curve, respectively, with each one following an independent square root process.

A2.2 The credit spread model

The most influential and representative papers on credit risk are the following. Jarrow and Turnbull (1995) draw an analogy between credit spread and foreign exchange rate, where a zero-coupon corporate bond can be converted into a zero-coupon government bond by the spot exchange rate derived on the condition of no prior default. Further, they assume the probability of default is independent of the constant recovery rate as well as the risk-free interest rate process, despite the fact that they are known to be correlated from empirical studies, such as Bakshi et al. (2006). Jarrow et al. (1997) extend and refine this model by assuming that the bankruptcy process follows a discrete state space and there exists a time-homogeneous Markov chain in credit ratings. In Duffie and Singleton (1999), when recovery rate is defined as a fraction of the market value rather than the face value or Treasury value in earlier reduced-form research, the credit spread y can be expressed as y(t) = h(t)(1-ω) in an equivalent martingale measure, where h(t) is the hazard rate and ω is the recovery rate in the risk-neutral world. In doing so, they can conveniently accommodate the default-adjusted short term rate (i.e. the sum of risk-free short rate and credit spread) with any desired risk-free term structure model. However, their method makes it difficult to decompose a credit spread into a hazard rate and a recovery rate and to model them separately. In order to overcome this problem, Bakshi et al. (2006) present a framework for studying the role of recovery rate on defaultable debt prices for a wide class of processes describing the recovery rates and default probability. These debt models have the ability to differentiate the impact of recovery rate and default probability on debt prices, and can be employed to infer the market expectation of recovery rates implicit in market prices. They are, therefore, able to model separately the recovery and hazard rate and allow a negative correlation between the two rates, which is found by their empirical work. In addition, Bakshi et al. (2006) find that the recovery specification relying on discounted face value provides a better fit to the data, when their defaultable debt models are tested using a sample of BBB-rated bonds.

Campbell and Taksler (2003) explore the effect of equity volatility on corporate bond yields. Panel data for the late 1990s show that idiosyncratic firm-level volatility can explain as much cross-sectional variation in yields as credit ratings. This finding supports Madan and Unal (1998), in which the authors decompose default risk into timing and recovery risks, and demonstrate that the default intensity process and, thus, the probability of default, is a function of the discounted equity value. Later Madan and Unal (2000) extend the process to a two-factor model including both non-interest sensitive asset value and risk-free interest rate processes. Their model allows stochastic interest rates to impact current asset values as well as their evolution, and generates credit spreads consistent with empirical observations.

Jarrow et al. (2010) develop a reduced-form approach for valuing callable corporate bonds by characterizing the call probability via an intensity process. Their approach extends the reduced-form model of Duffie and Singleton (1999) for defaultable bonds to callable bonds and captures some important differences between call and default decisions. A comprehensive empirical analysis of callable bonds shows that the reduced-form model by Jarrow et al. (2010) fits callable bond prices well and outperforms the traditional American option approach by Duffie and Singleton (1999) both in- and out-of-sample. Analogous to Duffie and Singleton (1999), Jarrow et al. (2010) jointly estimate the recovery rate and default intensity, and allow them to be correlated with the risk-free interest rate only. Tsiveriotis and Fernandes (1998) value a convertible bond with credit by separating it into two securities: a cash-only part of convertible bond (COCB) and an equity-like part convertible bond (ELCB). The holder of a COCB is entitled to all cash flows but no equity flows and, therefore, is subject to default, discounted at a risky rate (risk free + credit spread); conversely, the ELCB is default-free and discounted at a risk free rate. Since both parts are derivative securities with the same underlying stock, the COCB price and ELCB price can be calculated under the Black Scholes framework. However, the whole explanation on loss and recovery processes in case of default is missing from Tsiveriotis and Fernandes (1998), which does not say what actually happens to the convertible bond if default occurs. Takahashi et al. (2001) characterize default risk exogenously based on Duffie and Singleton (1999) and assume equity value itself is subject to default risk. They model the hazard rate as a decreasing function of stock price, hence naturally incorporating a negative relation between the probability of default and the level of stock price, and providing a consistent and practical reduced-form approach for relative pricing of securities including convertible and non-convertible corporate bonds and equities by treating the recovery rate as a constant. Ayache et al. (2002) argue that recovery to market value when default happens is not an optimal policy for the holders of convertible bonds, since the holders have the right to change the bonds to shares of stock - and, indeed, the model of Tsiveriotis and Fernandes (1998) is a special case of their optimal model.

A2.3 The liquidity spread model

Despite the large effort on credit risk modelling, little has been done for liquidity risk, which has gained increasing attention since the beginning of the 2007/2008 financial crisis in the credit markets. Aleksandrov and Hambly (2010) conclude that, along with credit risk, liquidity risk is very important and should not be underestimated. Longstaff et al. (2005) use the information in credit default swaps to obtain direct measures of the size of the default and non-default components in corporate spreads. They find that the majority of the corporate spread is due to default risk. This result holds for all rating categories and is robust to the definition of the risk-free rate curve. They also find that the non-default component is time varying, mean-reverting and strongly related to measures of bond-specific illiquidity as well as to macroeconomic measures of bond market liquidity. Furthermore, they only find weak evidence that the non-default component is related to the differential state tax treatment given to Treasury and corporate bonds. In their paper, Longstaff et al. (2005) specify the risk-neutral dynamics of the intensity process as square root and of the liquidity process as Gaussian; they assume the recovery rate is constant and there is an independence among risk free interest rate, default intensity and liquidity yield; and, finally, they derive a closed-form solution for corporate bonds, although they note that the in-sample correlations shows that these variables are not independent. Kempf and Uhrig-Homburg (2000) propose a theoretical continuous-time model to analyze the impact of liquidity on bond prices. This model values illiquid bonds relative to liquid bonds and provides a testable theory of illiquidity-induced price discounts. The empirical findings suggest that bond prices not only depend on the dynamics of interest rates but also on the liquidity of bonds. Thus, bond liquidity should be used as an additional pricing factor. The findings of the out-of-sample test demonstrate the superiority of the model over traditional pricing models without a liquidity factor. The authors use the square root dynamics for both risk free interest rate and liquidity discount, and solve the partial differential equation numerically after assuming a zero instantaneous correlation between them, similar to Longstaff et al. (2005). Kempf and Uhrig-Homburg (2000) also find from their empirical analysis that the correlation between the changes in the interest rate and changes in liquidity spread is significantly different from zero. Koziol and Sauerbier (2007) present an easily applicable option-theoretical approach to quantify liquidity spreads of corporate bonds. They describe the value of liquidity as that of multiple lookback options. After valuing these lookback options in a framework with uncertain interest rate, Koziol and Sauerbier (2007) find a liquidity factor is able to explain to a large part the empirically observed spreads, while credit risk has nearly no explanatory power for the bond prices. This is contradictory to what we usually find in the literature and explained by the authors thus: it is not easy to define those non-trading dates for illiquid bonds and the choice of those dates is important for the performance of their pricing model. Aleksandrov and Hambly (2010) suggest a framework for valuing defaultable bonds that allows for capturing not only the default risk but also the liquidity risk by expanding a credit intensity model. They then investigate defaultable bonds empirically and extract their liquidity risk within this model. Based on the dozens of corporate bonds in the finance industry, they observe a regime shift at the beginning of the credit crisis for the liquidity risk of a range of defaultable bonds. They also note that liquidity spread is very significant and is, in some cases, even larger than credit spread. Unfortunately, the authors ignore the dependence structure among risk free interest rate, default intensity and liquidity yield and also specify the dynamics of them as square root processes, hence eliminating the possibility of negative liquidity spread, which is found in Longstaff et al. (2005).

Empirical research supports the argument that a liquidity factor is significant in corporate bond pricing. A number of recent studies indicate that neither levels nor changes in the yield spread of corporate bonds over Treasury bonds can be fully explained by credit risk. For example, Chen et al. (2007) find that liquidity is priced in corporate yield spreads. Using a battery of liquidity measures covering over 4,000 corporate bonds and spanning both investment grade and speculative categories, they find that more illiquid bonds earn higher yield spreads and an improvement in liquidity causes a significant reduction in yield spreads. They find that liquidity is a key determinant in yield spread, explaining as much as half of the cross-sectional variation in yield spread levels and as much as twice the cross-sectional variation in yield spread changes than is explained by credit rating effects alone. Their findings justify the concern in the default risk literature that neither the level nor the dynamics of yield spreads can be fully explained by default risk determinants. Li et al. (2009) provide a comprehensive empirical analysis of the effects of liquidity and information risks on expected returns of Treasury bonds. They document a strong positive relation between expected Treasury returns and liquidity and information risks, controlling for the effects of other systematic risk factors and bond characteristics. This relation is robust to many empirical specifications and a wide variety of traditional liquidity and informed trading proxies.

Chapter A3. Methodology Review

In this section, I review the valuation models on different assumptions of the dynamics of pricing factors: risk free interest rate, default intensity and liquidity yield. Unless otherwise defined, a general debt asset is maturing in time T, paying a principal B at maturity if still alive on that date, paying a fixed coupon amount c at times t_i. It may be callable by the issuer at a price B_c at any time after the call date T_c, convertible at any time after the conversion date T_{cv} to k shares of stock with price S, and the spot interest rate is denoted by r.

A3.1 Simple independent world

Kempf and Uhrig-Homburg (2000) model the dynamics of interest rate and liquidity yield as square root processes, Aleksandrov. and Hambly (2010) define the dynamics of interest rate, default intensity and liquidity yield as square root, which avoids negative values and is a good choice for interest rate and default intensity modelling. However, as noted by Longstaff et al. (2005) and Fernandez (2005), liquidity spread can sometimes be negative; one possible reason is that investors prefer to hold long term bonds even if their returns are low. Longstaff et al. (2005) therefore assume that the risk-neutral dynamics of the liquidity process γ_t as

$$d\gamma = \eta dZ_\gamma$$

Where η is a positive constant and Z_γ is a standard Brownian motion. These dynamics allow the liquidity process to take on both positive and negative values. The authors also explore alternative specifications for that allow for a mean-reverting drift but these specifications generally do not perform better. In addition, the risk-neutral dynamics of the intensity process λ_t is

$$d\lambda = (\alpha - \beta\lambda)dt + \sigma\sqrt{\lambda}dZ_\lambda$$

Here α, β and σ are positive constant, and Z_λ is another Brownian motion. These dynamics allow for both mean reversion and conditional heteroskedasticity in corporate spreads, and guarantee that the default intensity process is always nonnegative. Define the value of a riskless zero-coupon bond D(T) with maturity T by

$$D(T) = \mathrm{E}\left[\exp\left(-\int_0^T r_t dt\right)\right]$$

A bondholder recovers a fraction 1-w of the par value of the bond in the event of default. The value of a corporate bond is given by a closed form solution under the independence assumption:

$$\begin{aligned} CB(c,w,T) &= c\int_0^T A(t)\exp\left(B(t)\lambda\right)C(t)D(t)e^{-\gamma t}dt \\ &+ A(t)\exp(B(T)\lambda)C(T)D(T)e^{-\gamma T} + (1-w)\int_0^T \exp(B(t)\lambda)C(t)D(t)(G(t)+H(t)\lambda)e^{-\gamma t}dt \end{aligned}$$

Where λ and γ denote the current values of the intensity and liquidity process, respectively, and

$$A(t) = \exp\left(\frac{\alpha(\beta+\phi)}{\sigma^2}t\right)\left(\frac{1-\kappa}{1-\kappa e^{\phi t}}\right)^{2\alpha/\sigma^2}$$

$$B(t) = \frac{\beta-\phi}{\sigma^2} + \frac{2\phi}{\sigma^2(1-\kappa e^{\phi t})}$$

$$C(t) = \exp\left(\frac{\eta^2 t^3}{6}\right)$$

$$G(t) = \frac{\alpha}{\phi}(e^{\phi t} - 1)\exp\left(\frac{\alpha(\beta+\phi)}{\sigma^2}t\right)\left(\frac{1-\kappa}{1-\kappa e^{\phi t}}\right)^{\frac{2\alpha}{\sigma^2}+1}$$

$$H(t) = \exp\left(\frac{\alpha(\beta+\phi)+\phi\sigma^2}{\sigma^2}t\right)\left(\frac{1-\kappa}{1-\kappa e^{\phi t}}\right)^{\frac{2\alpha}{\sigma^2}+2}$$

$$\phi = \sqrt{2\sigma^2 + \beta^2}$$

$$\kappa = (\beta+\phi)/(\beta-\phi).$$

For callable corporate bonds, Duffie and Singleton (1999) propose valuing them as American options written on otherwise identical non-callable bonds values using a reduced-form approach. This assumes that the firm calls the bond to minimize the market value of the particular bond under analysis; however, as argued by Jarrow et al. (2010), this assumption ignores the bond's impact on the firms' remaining liabilities and, hence, shareholders' equity might not be maximized. Alternatively, Jarrow et al. (2010) develop a reduced-form approach for valuing callable corporate bonds by characterizing the call probability via an intensity process, analogous to that of default intensity.

$$(1-k)\lambda_{c,t} = \alpha_c + h_{c,t} + \phi(c, s_{1,t}, s_{2,t})$$

Where k is the ratio of recovery to the market value of the bond when call action occurs, $\lambda_{c,t}$ is the call intensity, α_c is a constant to permit a non-zero call spread even for firms with close-to-zero call risk, $s_{1,t}, s_{2,t}$ represent the slope and level of the Treasury yield curve, respectively, the systematic component $\phi(c, s_{1,t}, s_{2,t})$ captures the portion of the standard call spread, and the idiosyncratic component $h_{c,t}$ captures the extra part that cannot be explained by the standard call spread. By carefully choosing parsimonious representations for the systematic and idiosyncratic component, the authors are able to derive a closed-form approximation for callable bond prices. Specifically

$$\phi(c, s_{1,t}, s_{2,t}) = \beta_{c1}(s_{1,t} - \bar{s}_1) + \beta_{c2}\frac{c}{s_{2,t}}$$

where c is the coupon rate of the callable bond and $\bar{s}_1$ is the average of slope factor of the Treasury yield curve. This specification captures the idea that, all else equal, a high-coupon bond is more likely to be called than a low-coupon bond and all callable bonds are more likely to be called when interest rates are low. Moreover, the nonlinear functional form of $\frac{1}{s_{2,t}}$ captures the nonlinear dependence of the call spread on interest rates. The idiosyncratic component follows an independent square root process,

$$dh_{c,t} = \kappa_c(\theta_c - h_{c,t})dt + \sigma_c\sqrt{h_{c,t}}\,dZ_{c,t}$$

The authors find the liquidity premium is insignificant after adding a liquidity spread to their pricing model and specifying the liquidity process as another independent square root process, although they note that the liquidity process is mean reverting and there is a negative risk premium associated with liquidity risk.

A3.2 Advanced correlated world

Duffee (1999), Jarrow et al. (2010) use a two-factor affine model for the spot risk-free interest rate

$$r_t = \alpha_r + s_{1,t} + s_{2,t}$$

where α_r is a constant, $s_{1,t}, s_{2,t}$ represent the slope and level of the Treasury yield curve, respectively. The dynamics for each of the two factors follow a square root process

$$ds_{i,t} = \kappa_i(\theta_i - s_{i,t})dt + \sigma_i \sqrt{s_{i,t}}\, dZ_{i,t}, \text{ for i=1, 2}$$

Here $Z_{i,t}$ is an independent standard Brownian motion. Jarrow et al. (2010) then model the default spread by the following representation:

$$(1-\delta)\lambda_{d,t} = \alpha_d + h_{d,t} + \beta_{d1}(s_{1,t} - \bar{s}_1) + \beta_{d2}(s_{2,t} - \bar{s}_2)$$

and

$$dh_{d,t} = \kappa_d(\theta_d - h_{d,t})dt + \sigma_d \sqrt{h_{d,t}}\, dZ_{d,t}$$

Where $Z_{d,t}$ is independent of $Z_{i,t}$. By this setting, default spread is naturally connected with Treasury rate and so is the call spread. In their empirical analysis of the importance of a liquidity premium, the authors ignore the influence of default intensity and Treasury rate on the liquidity process by letting the liquidity spread l_t follow another independent square-root process

$$dl_t = \kappa_l(\theta_l - l_t)dt + \sigma_l \sqrt{l_t}\, dZ_{l,t}$$

Following Lando (1998), Duffie and Singleton (1999), Jarrow et al. (2010), the price of a zero-coupon corporate bond CB(c,w,T) can be expressed as[2]

$$CB(c,w,T) = \mathrm{E}\left[\exp\left(-\int_0^T (r_t + \lambda_t(1-w) + \gamma_t)dt\right)\right]$$

There are two potential methods to impose a dependence structure on the dynamics of interest rate, default intensity and liquidity processes. One method is to relax the independence assumption, and specify their dynamics as

$$dr = (\alpha_r - \beta_r r)dt + \sigma_r \sqrt{r} dZ_r$$

$$d\lambda = (\alpha_\lambda - \beta_\lambda \lambda)dt + \sigma_\lambda \sqrt{\lambda} dZ_\lambda$$

$$d\gamma = \sigma_\gamma dZ_\gamma$$

Where $\rho(dZ_{r,t}, dZ_{d,t}) = \rho_{r,d} \neq 0, \rho(dZ_{r,t}, dZ_{l,t}) = \rho_{r,l} \neq 0$, and $\rho(dZ_{d,t}, dZ_{l,t}) = \rho_{d,l} \neq 0$.

AÏT-Sahalia (2008) provides closed-form expansions for the log-likelihood function of multivariate diffusions sampled at discrete time intervals. The coefficients of the expansion are calculated explicitly by exploiting the special structure afforded by the diffusion model. After achieving an

[2] It is straightforward to value a coupon bond given the price of a zero-coupon bond by treating a coupon bond as a portfolio of zero-coupon bonds.

approximated transition function $\widetilde{p}_{r,\lambda,\gamma}(t)$, we can value the corporate bond with a closed-form solution.

The other method is, analogous to Jarrow et al. (2010), to model the default spread and liquidity spread as functions of Treasury rate. Specifically, spot interest rate is modelled as

$$r_t = \alpha_r + s_{1,t} + s_{2,t}$$

where

$$ds_{i,t} = \kappa_i(\theta_i - s_{i,t})dt + \sigma_i\sqrt{s_{i,t}}dZ_{i,t}, \text{ for i=1, 2.}$$

Here, $Z_{i,t}$ is an independent standard Brownian motion. Default spread is

$$(1-w)\lambda_t = \alpha_d + h_{d,t} + \beta_{d1}(s_{1,t} - \bar{s}_1) + \beta_{d2}(s_{2,t} - \bar{s}_2)$$

and

$$dh_{d,t} = \kappa_d(\theta_d - h_{d,t})dt + \sigma_d\sqrt{h_{d,t}}dZ_{d,t}$$

where $Z_{d,t}$ is independent of $Z_{i,t}$. Finally liquidity spread is

$$\lambda_t = \alpha_l + h_{l,t} + \beta_{l1}(s_{1,t} - \bar{s}_1) + \beta_{l2}(s_{2,t} - \bar{s}_2)$$

and

$$dh_{l,t} = \kappa_l(\theta_l - h_{l,t})dt + \sigma_l dZ_{l,t}$$

where $Z_{l,t}$ is independent of $Z_{i,t}$ and $Z_{d,t}$. Here, systematic factors in the liquidity process are included and the liquidity process is simple Gaussian for two reasons. First, empirical research has found that the change of Treasury rate and that of liquidity spread are correlated - see Kempf and Uhrig-Homburg (2000), and Longstaff et al. (2005). By the above specifications, default spread and liquidity spread are connected exogenously. Second, liquidity spreads are mean-reverting and can take on both positive values and negative values by following the Ornstein–Uhlenbeck process. A closed form solution can, therefore, be derived since $Z_{l,t}$, $Z_{i,t}$ (i=1,2) and $Z_{d,t}$ are independent given the affine model structure.

The same argument can be applied to convertible bonds, Takahashi et al. (2001) explicitly take default risk into consideration based on Duffie and Singleton (1999), and provide a consistent and practical method for convertible bonds pricing. An associated partial differential equation is derived as

$$\frac{1}{2}\sigma^2 S^2 V_{ss} + (\alpha(S,t) + \lambda(S,t))SV_S + V_t - (r(t) + w\lambda(S,t))V + c(t) = 0$$

where c is the coupon.

In sum, numerous empirical studies have found the following phenomena:

- Equity volatility helps to explain default spread, see Campbell and Taksler (2003);
- Recovery rates are negatively associated with default probability, see Bakshi et al. (2006);
- Hazard rate should be a decreasing function of stock price, the probability of default is negatively related with the level of stock

price, see Takahashi et al. (2001).

- Treasury rate, default intensity and liquidity premium are correlated, see Longstaff et al. (2005).

For example, to capture the negative correlation between recovery rate and default probability, Bakshi et al. (2006) assume that the recovery rate is related to the hazard rate as

$$w(t) = w_0 + w_1 e^{-\lambda(t)}$$

And hazard rate is linear in the short interest rate

$$\lambda(t) = \Lambda_0 + \Lambda_1 r(t)$$

Here, the change of r follows a square-root process. To capture the decreasing relation between hazard rate and stock price, Takahashi et al. (2001) take the function

$$\lambda(S_t) = \theta + \frac{c}{S_t^b}$$

Therefore, an ideal model should (i) reflect those findings listed above, and (ii) allow a tractable solution, such as a closed or semi-closed form approximation, or have a fast convergence rate if numerical methods apply.

Chapter A4. CDS Valuation Review

Given the critical role of CDS contracts in this thesis, it is necessary to summarize influential approaches in the literature on valuation of CDSs and how these take into account the relationship between default and liquidity components. Three research branches existing in the current literature are briefly summarized in this chapter and more detailed review will be undertaken in Chapter B and C separately.

- Reduced form. Longstaff et al. (2005) assume a premium is paid continuously. By setting the values of the premium leg and protection leg equal to each other, they are able to value CDS spreads in a closed form solution. Pan and Singleton (2008) apply a reduced form model to Mexico, Turkey, and Korea sovereign CDSs, showing that a single-factor model for default spread following a lognormal process captures most of the variation in the term structures of spreads. Nashikkar et al. (2011) assume a constant default process and calculate CDS par yield in a reduced-form framework. Chen et al. (2008) assume risk-free rates and default rates are correlated and solve the CDS pricing model using a reduced-form model. Lin et al. (2011) value corporate bonds and CDSs simultaneously using a reduced form model, for CDS part, the authors assume there are both default and non-default part, and solve the model by assuming the two parts are independent. Jankowitsch et al. (2008) attribute the difference between corporate bond yields and CDS premium to one covenant of a CDS: cheapest-to-deliver option, and solve the covenant by relating it to recovery rate. Their empirical analysis does not support a liquidity premium. Carr and Wu (2010) propose a dynamically consistent framework that allows joint valuation and estimation of stock options and credit default swaps written on the same reference company. By assuming the stock price follows a jump-diffusion process with stochastic volatility and that the instantaneous default rate and variance rate follow a bivariate continuous process, the authors solve the reduced form model analytically. Brigo and Alfonsi (2005) introduce a two-dimensional correlated square-root diffusion (SSRD) model for interest-rate and default process, then value a CDS via Monte Carlo simulation. Zhang (2008) uses a three-factor model, namely interest rates, firm-specific distress variable, and hazard rate. He is able to link hazard rate with interest rate by assuming the former is a function of the latter, and then he solves the model analytically and applies it to Argentina sovereign CDSs.

- Structural model. The pioneering research on the structural model of default comes from Merton (1974) and Black and Cox (1976) and is summarized by RiskMetrics (2002). Zhong et al. (2010) argue a CDS is similar to out-of-the-money put options in that both offer low cost and effective protection against downside risk. They conclude that the put option implied volatility is an important determinant of CDS spreads. Bedendo et al. (2009) use an extended version of RiskMetrics (2002) to find that the gap between the model CDS premium and market premium is time-varying and widens substantially in times of financial turbulence. The authors note that CDS liquidity shows a significant impact on the gap and should, therefore, be included when pricing CDS contracts.

- CAPM framework. Valuation of CDS spreads under the Capital Asset Pricing Model (CAPM) framework is rather new and developing. It was pioneered by Bongaerts et al. (2011) and these authors imply that the equilibrium expected returns on the hedge assets can be decomposed into several components: priced exposure to the non-hedged asset returns, hedging demand effects, an expected illiquidity component, liquidity risk premium and hedging transaction costs. They then estimate CDS spread under market equilibrium.

Chapter A5. Conclusion

The financial crisis beginning in 2007 inspires new research on default risk, how to reflect the reality before and after the financial crisis more accurately is challenging and increasingly important. In this chapter I introduce the motivation of this thesis under such a volatile financial market, the research questions of this thesis and why they are important. To fill the literature gap, I then review the models and methodologies widely applied for default research, with a concentration on CDS valuation.

In summary, two widely traded CDS contract types are corporate and sovereign CDS, the first hedges against the default risk of a company and the second type hedges against the default risk of a sovereign country. Generally the research on CDS valuation can be classified into three dimensions: reduced form model, structural form model and CAPM framework model. A detailed overview is undertaken by Brigo et al., (2012). So the Chapter B examines the determinants of corporate CDS spreads from a structural form model point of view, with a concentration on the role of liquidity risk; and the Chapter C investigates the determinants of sovereign CDS spreads mostly from a reduced form point of view. The research using a CAPM framework will be beyond the scope of this thesis and will be my future research.

Part B: Regime Dependent Liquidity Determinants of Credit Default Swap Spread Changes

Abstract B

In this section I construct a liquidity measure for Credit Default Swaps (CDS) and investigate the relationship between the changes in CDS spreads and the determinants implied by structural models of default, including firm leverage, volatility, risk-free interest rate, and liquidity. Using a dummy-variable pooling regression and a Markov regime switching model, I find strong evidence that these determinants, especially the liquidity determinant, are significant and time-varying. Among the four determinants, the effects of liquidity shock on CDS spreads differ significantly across rating groups when the CDS market is tranquil but when it is turbulent the effects become similar, regardless of credit rating.

Chapter B1. Introduction

A credit default swap (CDS) is a contract in which the buyer of protection makes a series of payments, often referred to as CDS spreads, to the protection seller and, in exchange, receives a payoff if a default event occurs. CDSs have existed since the early 1990s and the market increased greatly from 2003, such that by the end of 2007 the outstanding notional amounts were $62.2 trillion, falling to $30.4 trillion by the end of 2009. The corresponding amounts for total equity derivatives were $10.0 trillion and $6.8 trillion (ISDA Market Survey, 2010). Understanding the variation of CDS spreads has become important for investors, given the large market size and the hedging function of CDSs against default.

In this chapter I investigate the relationship between the changes in CDS spreads and the determinants implied by structural models of default. It is acknowledged in the literature that CDS spreads are superior to corporate bond spreads for default research through more accurate data and higher trading frequency. Empirical studies focus on analyzing three determinants suggested by the pioneering model of Merton (1974), namely leverage ratio, volatility and risk-free rate (Collin-Dufresne et al., 2001; Campbell and Taksler, 2003; Zhang, 2008; Zhang et al., 2009; Ericsson et al.. 2009; Zhong et al., 2010). Recent research provides both a theoretical foundation and evidence that liquidity is priced in CDS spreads (Ericsson and Renault, 2006; Bedendo et al., 2011; Bongaerts et al., 2011; Bhanot and Guo, 2012; Pu et al., 2011). In particular, Ericsson and Renault (2006) develop a structural model for both liquidity and credit risk, and Bongaerts et al. (2011) derive an equilibrium asset pricing model incorporating liquidity. Their results are important since they demonstrate how a model with a fourth determinant, liquidity, could improve the understanding of the nature of CDS spreads.

The financial crisis that began in 2007 has changed financial markets dramatically. For example, Figure 1 plots the average CDS spreads in my sample - clearly spreads behave differently after June, 2007, when the financial crisis began. Underlying determinants of CDS spreads may differ in their effects when the CDS market is in either tranquil or turbulent circumstances. Therefore, I am motivated to examine the four determinants both unconditionally and conditionally by using recent US corporate CDS data. Proxies for the leverage ratio, volatility and risk-free rate are standard and I construct a liquidity measure for CDS at a market level analogous to the measure for corporate bond proposed by Bao, et al. (2011). I then conduct tests on the significance and time-varying magnitude of these determinants by a dummy-variable pooling regression and a Markov regime switching model, with emphasis on the liquidity determinant.

Two main results emerge from the analysis. First, unconditionally, by regressing the daily changes in 5-year senior unsecured debt CDS spreads from January 2004 to June 2010 on the changes in leverage ratio, volatility, risk-free rate and liquidity, I find the coefficients for all four determinants are statistically significant. These findings hold after controlling for other explanatory variables implied by extended structural models of default such as the changes in treasury yield curve slopes, jump magnitudes, business climate, and nonlinear effects of Treasury yields. Second, conditionally, both the dummy-variable pooling regression and the standard Hamilton (1989) Markov two-regime switching model indicate that these determinants are indeed time-varying. The crisis dummy variable is strongly significant for all CDSs, suggesting that the crisis shifts the level of the change in CDS spreads. In addition, the significant interaction terms between the crisis dummy variable and the four determinants indicate the slope sensitivities change dramatically during the crisis.

Figure 1. The Average of All CDS spreads (%)

Note: Y axis is CDS spreads (%) and X axis is date.

Furthermore, the regime switching model finds that the effect of liquidity is more pronounced in crisis regime than in normal regime; specifically, the coefficient for liquidity determinant represented by my liquidity measure in crisis regime is 17.07 times as large as that in normal regime, compared with the 3.22, 2.73, and 3.56 times for leverage ratio, volatility and risk-free rate, respectively. A t-test strongly rejects the coefficients of the determinants being equal between regimes. The intuition of applying a regime switching model is that, due to the financial crisis, determinants may change in their shocks to CDS spreads. We may ask whether the statistical significance of these determinants is robust under different market conditions, when the CDS market is in either 'normal' or turbulent circumstances. From an economic perspective, it is reasonable to believe that the effect of liquidity on default spreads can be small when the financial market is healthy and can be high when the market is in danger. As an illustration, Figure 1 clearly shows spreads behave differently after the financial crisis began.

My work is most closely related to Pu et al. (2011) and Alexander and Kaeck (2008). Pu et al. (2011) find evidence that liquidity is priced in CDSs unconditionally; however, the sample is restricted to monthly data from January 2001 to December 2007 and so does not fully cover the financial crisis, which restricts conducting a conditional analysis. Alexander and Kaeck (2008) employ a similar Markov regime switching model for the iTraxx Europe CDS index from June 2004 to June 2007 and so they are unable to distinguish the influences on different credit rating classes of reference entities; moreover, they do not explicitly take a liquidity determinant into account.

The structure of the Chapter is as follows. Chapter B2 reviews literature on the developments of the determinants of corporate CDS, with emphasis on liquidity determinant. Chapter B3 presents the regression models including standard univariate and multivariate ordinary least square regressions (OLS), dummy variable regression and Markov regime switching regression. Chapter B4 reports the data set and summary statistics. The empirical results and discussion are presented in Chapter B5, in which I explain the results I find, discuss their economic meaning, and conduct robustness tests, followed by conclusions in Chapter B6.

Chapter B2. Literature Review

Pioneered by Merton (1974), the basic structural model of default and its extensions have become a standard for default spread analysis. While these models have their own theoretical variables or functional forms, typically they have common variables that are central to determine the changes of default spreads. Merton (1974) values a defaultable risky asset as a risk-free asset less a put option on the issuing firm's value; as a result, three core determinants are leverage ratio, risk free rate, and volatility. Leverage ratio measures the distance to the strike price (the issuing firm's value) of a put option and the likelihood of triggering default; risk free rate decides the value of a risk free asset; and volatility determines the value of a put option. Collin-Dufresne, Goldstein et al. (2001) regress the changes of corporate bond yield spreads on variables that should determine credit spread changes in the theory of structural models of default, including leverage ratio, volatility, and risk free rate. They find those variables are statistically significant. Using similar variables but with the change of CDS spreads instead of the change of corporate bond yields spreads as a dependent variable, Ericsson, Jacobs et al. (2009) draw an identical conclusion that the variables suggested by the basic structural model pioneered by Merton (1974) are crucial to explain the changes of CDS spreads, even after controlling for extra variables of extended structural models. Boss and Scheicher (2002) investigate the determinants of credit spread changes in the euro area and conclude leverage, volatility and risk-free rate are important factors. Avramov, et al. (2007) provide further evidence that a parsimonious set of common factors including leverage, volatility and spot rate are able to explain more than 54% of the variance in credit spread changes.

Among the three core determinants, leverage ratio has long been an important determinant for debt research. All else equal, the higher leverage ratio is, the higher is the risk of default and the larger is default spread. Therefore, credit spread should increase as the leverage ratio increases. For example, Collin-Dufresne and Goldstein (2001) propose a structural model of default that captures the change of debt levels in response to changes in firm value; furthermore, their model generates mean-reverting leverage ratios. They find the credit spreads their model generates are more consistent with empirical findings, which suggests a critical role of leverage ratio in explaining credit spread. Both Collin-Dufresne, Goldstein et al. (2001) and Ericsson, Jacobs et al. (2009) find that credit spread is an increasing function of leverage ratio via a regression. Cesare and Guazzarotti (2010) analyse the determinants of credit default swap spread changes between Janauary 2002 and March 2009. They document that the spreads have become much more sensitive to the level of leverage since the breakout of the financial crisis.

All else equal, the higher volatility is, the higher is the risk of default and, thus, the larger is default spread. Therefore, credit spread should increase as volatility increases. Campbell and Taksler (2003) explore the effect of equity volatility on corporate bond yields and find equity volatility is a significant factor in explaining the cross-sectional variation in yields. Benkert (2004) investigates the effects of equity volatility on credit default swap premia and finds evidence that option-implied volatility is an important factor in explaining variation in CDS spreads, using panel data of CDS on 120 international firms from 1999 to mid-2002. Zhang et al. (2009) explain CDS spreads by volatility and jump risk of equity prices. Zhong et al. (2010) argue that a CDS is similar to an out-of-the-money put option in that both offer a protection against downside risk, their result indicates the put option implied volatility is an important determinant of CDS spreads. Again, both Collin-Dufresne, Goldstein et al. (2001) and Ericsson, Jacobs et al. (2009) find, via regression, that credit spread is an increasing function of volatility.

All else equal, the higher risk-free rate is, the lower is the risk of default and, thus, the smaller is default spread. Therefore, the credit spread should decrease as risk-free rate increase. Longstaff and Schwartz (1995) argue that an increase in risk-free rate increases a company's value which, in turn, decreases the probability that the value of the company will fall below the default threshold and, consequently, reduces the default risk and leads to a smaller credit spread. Based on that argument, they test empirically the negative relationship between risk-free rates and credit spreads. Duffee (1998) provides further evidence that changes in credit spreads and interest rates are negatively related by testing a sample of non-callable bonds.

Besides the three core determinants, other variables are found to be significant in explaining credit spreads by an extended structural model of default. For instance, Fama and French (1989) argue that an increase in the yield-curve slope suggests an improvement of economy, which leads to higher recovery rates and lower credit spreads. Litterman and Scheinkman (1991) find that an increase in the slope also increases the expected future spot rate, and then a steeper slope leads to a decrease in credit spreads. Altman and Kishore (1996) argue that an improving economy narrows credit spreads. Zhang (2008) finds that the default risk premium in a CDS is affected by business cycle, credit conditions and the overall strength of economy. Collin-Dufresne, Goldstein et al. (2001) and Ericsson, Jacobs et al. (2009) investigate jumps in firm value and square of risk-free rate as extra determinants of credit spreads. They argue that a larger jump in firm value increases the probability of default and leads to a higher credit spread, while adding the square of risk-free rate controls the possible nonlinear relationship between credit spread and risk-free rate.

All the above mentioned papers do not explicitly consider liquidity as a determinant. However, researchers started to realize that liquidity is significant for CDS valuation. Longstaff et al. (2005) find that non-default components in corporate bond credit spreads are strongly related to liquidity measures. Tang and Yan (2007) present an empirical study of the pricing effect of liquidity in the CDS market and find evidence that liquidity risk is priced in CDS spreads. Buhler and Trapp (2006, 2008) explicitly incorporate a liquidity intensity rate process into their reduced form models. Pan and Singleton (2008) examine the term structure of sovereign CDS spreads and claim that a second principal component (possibly related to the liquidity spread) is needed to explain the severe mispricing of one-year contracts. More recently, Bhanot and Guo (2011) show that the deviations between the CDS spread and corporate bond spread can be explained by funding liquidity and asset-specific liquidity. Bedendo, Cathcart et al. (20011) demonstrate that liquidity in the CDS market should be taken into account when pricing CDS contracts. Bongaerts, de Jong et al. (2011) derive an equilibrium asset pricing model incorporating liquidity and find an economically small but significant effect of liquidity for CDS market. Ericsson and Renault (2006) develop a structural model for both liquidity and credit risk, and find evidence of a liquidity component of yield spreads.

Annaert et al. (2013) decompose the CDS spread changes of 32 listed Euro area banks and find evidence that liquidity-related variables complement credit-related variables in explaining credit spread changes. All else equal, the higher illiquidity is, the higher is the risk of default and, thus, the higher is default spread. Therefore, the credit spread should increase as liquidity becomes worse.

Table 1 summarizes the predicted sign of the correlation between changes in credit spreads and changes in the main determinants I investigate in this work.

Table 1. Expected Sign between Changes in Credit Spreads and Determinants

Determinant	**Predicted sign**
Leverage ratio	+
Volatility	+
Risk-free rate	-
illiquidity	+

Chapter B3. Theoretical Determinants of Spread Changes and Regression Models

Following the structural model of default of Merton (1974), in default spread analysis three core determinants are used: leverage ratio, risk-free rate and volatility. Huang and Huang (2002) show that credit risk accounts for only a small fraction of the observed yield spreads by calibrating a wide class of structural models to historical default loss data. Detailed empirical testing of five structural models is undertaken by Eom et al. (2004) using a sample of 182 bond prices from 1986-1997, in which the authors find that all five models have substantial spread prediction errors. In light of the shortcomings of existing structural models, Ericsson and Renault (2006) develop a new structural model to capture simultaneously liquidity and credit risk, and they find evidence of a correlation between the liquidity and default components of yield spreads. Hence, my ordinary least squares (OLS) multiple regression model with a liquidity determinant is

$$\Delta S_t = \alpha + \beta_1 \Delta \mathrm{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta \mathrm{VOL}_t + \beta_4 \Delta \mathrm{L}_t + \varepsilon_t \tag{1}$$

where α is an intercept,ΔS_t, $\Delta \mathrm{LEV}_t$, Δr_t, $\Delta \mathrm{VOL}_t$, $\Delta \mathrm{L}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively, at *t*.

To take into account the shortcomings of the standard structural model, I control for several additional variables implied by extended structural models. I estimate the full regression model suggested by Collin-Dufresne et al. (2001) and Ericsson et al. (2009),

$$\Delta S_t = \alpha + \beta_1 \Delta \mathrm{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta \mathrm{VOL}_t + \beta_4 \Delta \mathrm{L}_t + \beta_5 \Delta r_t^2 + \beta_6 \Delta \mathrm{slope}_t + \beta_7 \Delta \mathrm{S\&P}_t + \beta_8 \Delta \mathrm{jump}_t + \varepsilon_t \qquad (2)$$

where the square of risk-free rate, r_t^2 is included to capture the nonlinear relationship between default spreads and risk-free rates; slope_t represents the difference between the long-term (10-year) and short-term (2-year) risk-free rate in order to estimate the instantaneous short rate; $\Delta \mathrm{S\&P}_t$ is the return of the S&P 500 to reflect the overall state of the economy; jump_t is a proxy for jumps in firm value to control for the effect of probability and magnitude of a jump on credit spread. Since we can't observe directly a jump variable for all entities, I approximate it as the slope of the smirk[3] of implied volatilities σ of European put options on the S&P 500 index. Define moneyness m_i=ln$\left(\frac{K_i}{S}\right)/\sqrt{T_i}$, where K_i is the strike price, S is the S&P 500 index value, T_i is the time to maturity of

[3] In the early option pricing models, a constant volatility is assumed as an input for the underlying asset. However, empirically, when price is used as an input and volatility as an output, this "implied volatility" is usually not constant. Plots of implied volatility versus distance in or out of the money (where current underlying price equal to the option's exercise price is "at the money") may be U-shaped – a "smile" – or somewhat less regular – a "smirk". This reflects the probability of extreme moves. The slope measures the steepness of volatility smirk and is an indicator of jump magnitude of an asset, the larger the slope is, the steeper the smirk and the higher probability of a jump in an asset's value will be.

a European option i on date t. The slope of the smirk b for date t is then estimated via an ordinary linear regression[4] $\sigma(m_i) = a + bm_i + \varepsilon$.

I adopt two models to examine the time-varying sensitivities of determinants. The first is a dummy-variable pooling regression method. I run the following pooling regression for the whole sample or for each credit rating class subsample:

$$\Delta S_t = \beta_0 + \beta_1 \Delta r_t + \beta_2 \Delta \mathrm{VOL}_t + \beta_3 \Delta \mathrm{LEV}_t + \beta_4 \Delta L_t + \delta_0 C + \delta_1 \Delta r_t C + \delta_2 \Delta \mathrm{VOL}_t C + \delta_3 \Delta \mathrm{LEV}_t C + \delta_4 \Delta L_t C + \varepsilon_t \quad (3)$$

where C is a dummy variable for crisis, with C=1 for sample dates during crisis, and C=0 otherwise. Whether the intercept shifts, and whether the slope sensitivities change during the crisis can, therefore, be examined by testing the significance of δ_0 for the dummy variable and $\delta_i, i \in (1,2,3,4)$ for the interaction terms via a standard partial F-test. Similarly, I can also test the effects of credit rating by running a pooling regression for the sample during or outside of crisis:

$$\Delta S_t = \beta_0 + \beta_1 \Delta r_t + \beta_2 \Delta \mathrm{VOL}_t + \beta_3 \Delta \mathrm{LEV}_t + \beta_4 \Delta L_t + \delta_{01} R_1 + \delta_{02} R_2 + \delta_{03} R_3 + \delta_{11} \Delta r_t R_1 + \delta_{12} \Delta r_t R_2 + \delta_{13} \Delta r_t R_3 + \delta_{21} \Delta \mathrm{VOL}_t R_1 + \delta_{22} \Delta \mathrm{VOL}_t R_2 + \delta_{23} \Delta \mathrm{VOL}_t R_3 + \delta_{31} \Delta \mathrm{LEV}_t R_1 + \delta_{32} \Delta \mathrm{LEV}_t R_2 + \delta_{33} \Delta \mathrm{LEV}_t R_3 + \delta_{41} \Delta L_t R_1 + \delta_{42} \Delta L_t R_2 + \delta_{43} \Delta L_t R_3 + \varepsilon_t \quad (4)$$

with R_1, R_2 and R_3 indicating credit rating dummy for credit rating classes obtained from the S&P credit rating agency: R_1=1 for any AA- ~ AAA rated

[4] A similar estimation method is applied by Ericsson et al. (2009) and Christoffersen et al. (2009).

CDS, R_2=1 for any A- ~ A+ rated CDS, R_3=1 for any BBB- ~ BBB+ rated CDS, and zero otherwise[5].

The second candidate is a Hamilton (1989) Markov two-regime switching model[6], allowing the intercept, the coefficients estimates for all explanatory variables, and the residual volatility to vary between the two regimes. The Markov regime switching regression model becomes

$$\Delta S_t = \alpha_i + \beta_{i,1}\Delta \mathrm{LEV}_t + \beta_{i,2}\Delta r_t + \beta_{i,3}\Delta \mathrm{VOL}_t + \beta_{i,4}\Delta \mathrm{L}_t + \varepsilon_{i,t} \tag{5}$$

where $i \in \{1, 2\}$ represents 2 regimes. A state variable s_t determines which regime it is at time t, and the probability of a transition or a stay in the same regime at time t+1 is only decided by the state at time t. I denote the Markov switching probability as:

$$P(s_t = 1 | s_{t-1} = 1) = p_{11}$$

$$P(s_t = 2 | s_{t-1} = 2) = p_{22} \tag{6}$$

then I am able to run a standard Markov regime switching model under the assumption of Gaussian $\varepsilon_{i,t}$ for both regimes. The Appendix B.A describes the steps.

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[5] It is a common practice in default research field to divide rating into four classes as AA- ~ AAA, A- ~ A+, BBB- ~ BBB+ and below BBB-.

[6] An N-regime switching model could have been used but interpretation is more natural for my purposes via a two-regime model and follows other literature, particularly, Alexander and Kaeck (2008) and Acharya et al. (2012).

Chapter B4. Data Description

B4.1 CDS data

I obtain daily 5-year senior unsecured single-name CDS spreads data from CMA via Datastream, from 05 January, 2004 to 30 June, 2010. CMA is the world's leading source of independent data on the OTC markets. I use 5-year mid-market CDS quotes because the 5-year CDS is widely believed to be more frequently traded compared with CDSs of other maturity. I include those CDSs in my sample by further imposing the following screening criteria:

a) Its reference entity must have data in CRSP and COMPUSTAT;
b) Its reference entity is not in the utilities or financial industries;
c) It must have at least one year of trading data;
d) Its spreads must change at least once out of 20 reported trading days (roughly one month) on average.

Criterion a) enables me to calculate explanatory variables such as the leverage ratios for regression; b) excludes CDSs of those companies in utilities and financial industries, since they have different corporate structures; c) excludes any CDS that disappears soon after listing or is of recent issue; d) removes any extremely inactive CDSs. This screening generates 311,545 CDS quotes issued by 242 reference entities. I then obtain the S&P credit rating for each entity from CRSP and compute the averaged rating for any entity with multiple rating records[7].

[7] In doing so, analogous to Pu et al. (2011), I allocate a number to each rating and calculate the average.

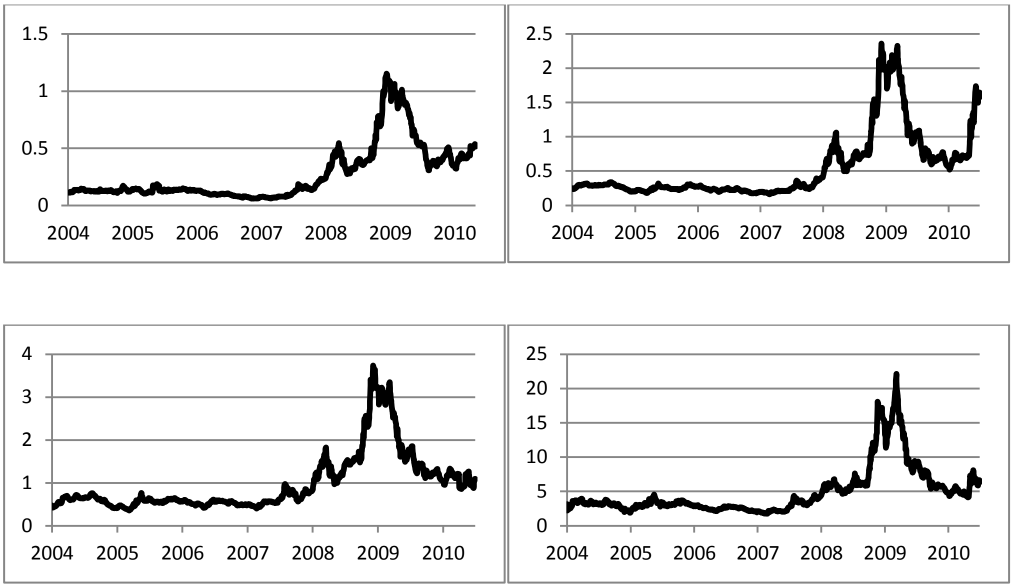
Table 2. Description of CDS Spreads

Panel A: Whole period	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB-	All
NumOb	1483.47	1360.48	1258.76	1209.39	1287.38
NumCompany	15.00	66.00	97.00	64.00	242.00
Mean (%)	0.28	0.55	1.04	5.17	1.87
Stdev (%)	0.27	0.80	1.30	7.05	4.11
5th Pctl (%)	0.05	0.13	0.24	0.79	0.13
95th Pctl (%)	0.85	1.68	3.25	16.77	6.90
Panel B: Normal period	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB-	All
NumOb	1110.47	1007.68	914.43	862.94	938.40
NumCompany	15.00	66.00	97.00	64.00	242.00
Mean (%)	0.18	0.35	0.72	3.56	1.26
Stdev (%)	0.14	0.39	0.78	3.67	2.30
5th Pctl (%)	0.05	0.12	0.22	0.68	0.12
95th Pctl (%)	0.48	0.83	1.85	9.73	4.88
Panel C: Crisis period	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB-	All
NumOb	373.00	363.83	367.03	363.49	365.60
NumCompany	15.00	64.00	91.00	61.00	231.00
Mean (%)	0.58	1.14	1.90	9.17	3.51
Stdev (%)	0.32	1.25	1.88	10.85	6.66
5th Pctl (%)	0.20	0.31	0.42	1.70	0.35
95th Pctl (%)	1.25	3.42	5.22	28.24	13.26

Note: NumOb, NumCompany, Mean, Stdev, 5th Pctl, 95th Pctl represents the average number of observations per CDS in that category, the total number of reference entities, mean CDS spreads, standard deviation of spreads, the 5th and 95th percentile of spreads in percentage, respectively. Panel A, B, and C present the statistics for the whole, normal and crisis period separately.

Table 2 reports a short description of the CDS spreads in my sample. The average number of observations per entity is close across credit rating, the average number of observations for the whole sample is 1287, indicating an entity has over five years CDS quotes history on average. Both the mean spreads and the standard deviation of spreads increase with lower credit rating; for example, the mean CDS spread for AA- ~ AAA entities is 28 basis points (bps) with a standard deviation of 27 bps, compared with the 517 bps mean spread and 705 bps standard deviation for below BBB- entities. Figure 2 illustrates these differences for each rating class. CDS spreads are lower and stable before the beginning of 2007, become volatile after the end of 2007 and reach their maximum around 2009, regardless of credit rating.

Figure 2. The Average CDS Spreads for Each Credit Rating Class (%)



Note: Graphs from top-left to bottom-right are the average CDS spreads for entities with credit rating AA- ~ AAA, A- ~ A+, BBB- ~ BBB+, and below BBB-, respectively. Y axis is CDS spreads (%) and X axis is date.

I collect data for the explanatory variables as follows: the market value of equity from CRSP, the book value of debt and of preferred equity from COMPUSTAT to calculate the leverage ratio; the VIX data from the Chicago Board Options Exchange (CBOE); both 10-year and 2-year Treasury yields from the Federal Reserve Bank; both the S&P 500 index levels and returns from CRSP; the volatility surface data for S&P 500 option from Option Metrics; and the 3-month Libor rates from Datastream.

B4.2 Determinants proxies

A good proxy for liquidity in my context should have the following characteristics: first, it is better if available at a daily frequency; second, it can be estimated from the CDS data[8]. In light of this, I construct a liquidity measure γ similar to the gamma measure for corporate bonds proposed by Bao, et al. (2011),

$$\gamma = \text{cov}(\Delta S_t, \Delta S_{t-1})$$

γ measures the covariance between consecutive CDS spread changes[9]. I use positive covariance instead of the negative sign in Bao et al. (2011) since, by definition, CDS spread is approximately the difference between bond yield and risk-free rate and its change is, therefore, negatively correlated with corporate bond price return. Higher γ indicates stronger illiquidity. I first calculate γ for each CDS and then use the cross-sectional median γ as the aggregate γ liquidity measure for the CDS market, analagous to Bao, et al. (2011).

8 CDS is an over-the-counter contract and its trading volume is unavailable from the data source, restricting the use of liquidity measures by Amihud (2002) and Pastor and Stambaugh (2003), both widely used in literature.

[9] Based on the model in Bao, et al. (2011), an asset's return Δp consists of two components $\Delta p_{\mathrm{t}} = \Delta \mathrm{f}_{\mathrm{t}} + \Delta \mathrm{u}_{\mathrm{t}}$, where the first component f_{t} represents the fundamental value without any friction and follows a random walk, the second component u_{t} is a transitory term uncorrelated with f_{t} and represents the impact of illiquidity. The covariance $\mathrm{cov}(\Delta p_{\mathrm{t}}, \Delta p_{\mathrm{t-1}})$ thus depends only on the transitory component and captures its magnitude.

The proxy for the risk-free rate is the 10-year Treasury bond yield and for volatility I use the VIX, a measure of the implied volatility of S&P 500 index options[10]. I define the leverage ratio as

$$\frac{\text{Book value of debt+Book value of preferred equity}}{\text{Market value of equity+ Book value of debt+Book value of preferred equity}}$$

which is a standard definition in asset default research, see Collin-Dufresne et al. (2001) and Ericsson et al. (2009). I linearly interpolate quarterly book values of debt and preferred equity in order to estimate daily leverage ratios[11], as all other variables are at a daily frequency.

Table 3 shows the summary statistics of those explanatory variables for my regression. The 2-year yields have a smaller mean value and a larger standard deviation than the 10-year yields. The spreads between 10-year and 2-year yields are mainly positive, their -0.11% 5th percentile shows there are

[10] Collin-Dufresne et al. (2001) use VIX data; Ericsson et al. (2009) use the individual firm's exponentially weighted moving averaged historical volatility; Zhong et al. (2010) find that the individual firm's implied volatility dominates historical volatility in explaining the time-series variation in CDS spreads. Since not all individual firm option data are available to me, in this chapter I use VIX data to proxy the volatility determinant.

[11] Instead of linearly interpolating the leverage ratios, I only interpolate quarterly book values of debt and preferred equity, then estimate the daily leverage ratio together with the daily market values of equity. Such an approximation allows the daily change of leverage ratio to be varied without suffering strong serial autocorrelation.

periods when short term yields become higher than long term yields. The leverage ratios, VIX, and S&P 500 index values have rather larger standard deviations than other variables, especially than the jumps, which are centred around the mean value. The last column reports the average of estimated time series correlation between CDS spreads and each explanatory variable across all entities. On average, CDS spreads are positively correlated with the leverage ratios, VIX, yield spreads, and γ, and are negatively correlated with the 2-year, 10-year yields, S&P 500 levels and returns, and jumps. CDS spreads have the highest positive correlation with the VIX, and the highest negative correlation with the 10-year yields, suggesting the importance of these two explanatory variables. Figure 3 plots the time series of the averaged CDS spreads against that of the leverage ratios, VIX, 10-year yields and γ[12]. CDS spreads moved closer with the VIX than with the leverage ratios around the break of credit crisis, since the VIX is more timely than the leverage ratios. It is obvious from the plots that CDS spreads are negatively related with 10-year yields and positively with γ. γ is stable before the end of 2007 and increases considerably after 2008, reflecting the illiquid market due to the financial crisis.

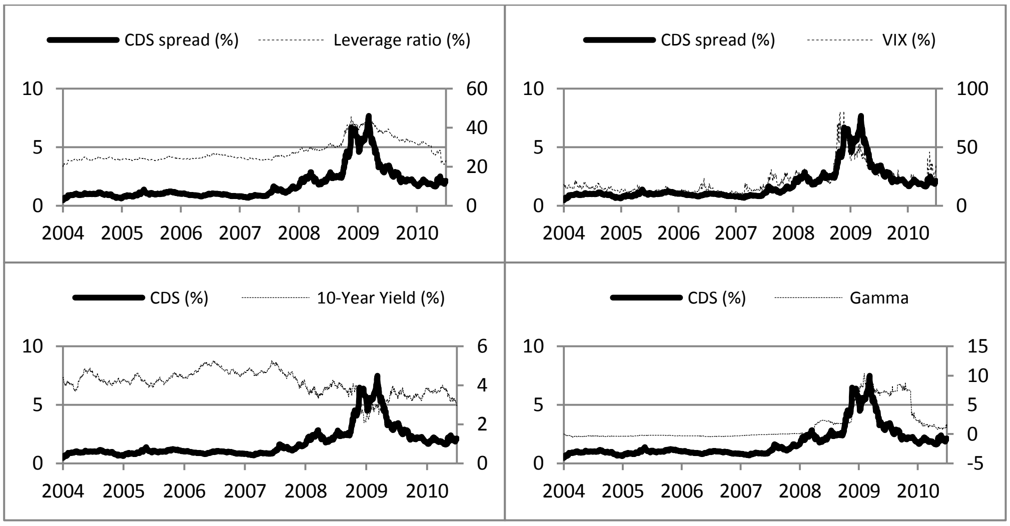
[12] I multiple γ by 10^8 to make the variable more pronounced.

Table 3. Description of All Explanatory Variables in Sample

	Mean	Stdev	5th pctl	95th pctl	time series corr
Leverage (%)	28.56	19.98	4.75	70.10	0.62
10-year yield (%)	4.12	0.64	2.87	5.07	-0.71
VIX (%)	21.15	11.91	10.87	46.67	0.75
Yield slope (%)	1.09	1.00	-0.11	2.72	0.52
2-year yield (%)	3.02	1.54	0.85	4.97	-0.64
S&P 500	1221.46	194.96	851.92	1511.04	-0.62
S&P 500 return (%)	0.00	1.44	-2.26	1.91	-0.01
Jump	-0.24	0.04	-0.30	-0.18	-0.17
Gamma	1.60	2.97	-0.40	8.16	0.63
Credit rating	3.87	1.07	2.00	6.00	

Note: Mean, Stdev, 5th Pctl, and 95th Pctl represents the mean values, the standard deviation, the 5th and 95th percentile of each variable, respectively. Variables in the first column include the leverage ratios, 10-year Treasury yields, VIX, spreads between 10-year and 2-year Treasury yields, 2-year Treasury yields, S&P 500 index values, S&P 500 returns, jumps in issuing firm's value, gamma (γ), and credit ratings of reference entities. Credit ratings range from 1 to 8, with 1 for "AAA", 2 for "AA- ~ AA+", 3 for "A- ~ A+", 4 for "BBB- ~ BBB+", 5 for "BB- ~ BB+", 6 for "B- ~ B+", 7 for "C ~ CCC+", and 8 for "D" and any rating else. The last column reports the average correlation between CDS spreads and the values of each explanatory variable across reference entities.

Figure 3. Time Series Plot of CDS Spreads Against Four Determinants



Note: For both graphs the left axis is for CDS spreads, the right axis is for the leverage ratios, VIX, 10-year treasury yields, and γ respectively from top-left to bottom-right.

Chapter B5. Empirical Results and Discussion

B5.1 OLS regression results

I run regression (1) and (2) for the changes in CDS spreads of each entity, then I calculate the averages of the regression results for all entities in the whole sample or in a credit rating class.

Panel A in table 4 presents the results of the multivariate regression (1). The t-statistic is computed based on the method in Collin-Dufresne et al. (2001)[13] in order to capture the cross-sectional variation in the time-series regression coefficient estimates. The leverage ratio, VIX, 10-year yield and γ remain statistically significant and, as expected, all coefficients estimates for the leverage ratio, VIX, γ are positive, and are negative for the 10-year yield. γ is strongly significant for all rating entities and its positive coefficients are consistent with the belief that decreasing market liquidity leads to an increase of CDS spread. The coefficient estimates become larger when the rating of entities is lower; for instance, on average a 1% increase in γ increases the CDS spread by approximately 0.21 bps for the AA- ~ AAA entities but by 5.81 bps for the entities below BBB-.

Panel B further reports the results of the multivariate regression (2) controlling for several additional variables. Sign, significance level, and magnitude of coefficient estimates for the leverage ratio, VIX, 10-year yield, and γ are similar to the results in regression (1). Jump in issuing firm value

[13] The t-statistic is calculated by dividing each averaged coefficient value by the standard deviation of the N estimates and multiplying $\sqrt{N}$, where N is the number of reference entities.

seems to have no impact on the changes in CDS spreads, its coefficients are insignificant. S&P 500 return is insignificant for all entities except A- ~ A+. Both the square of 10-year yield and the yield spread between 10-year and 2-year are insignificant at 5% significance level.

In summary, I find that these determinants, namely leverage ratio, volatility, risk-free rate and liquidity, are statistically significant in explaining the change in CDS spreads[14]. Adding a liquidity determinant helps in understanding the variation of CDS spreads. The change in CDS spreads is larger when the change in liquidity becomes bigger, and vice versa. The significance of the liquidity determinant is robust to controlling for other variables implied by extended structural models.

[14] The reported adjusted R^2 is slightly low, which is mainly because I use daily data for analysis as daily data is acknowledged to be noisier than monthly data. The adjusted R^2 for the whole sample becomes 31.09% when monthly data is applied; however, monthly data restricts the time-varying analysis due to its short sample size, which is the main purpose of this chapter's research. The strong significance of the explanatory variables, together with the high adjusted R^2 for CDS level regression, indicates their good explanatory power.

Table 4. Multivariate OLS Regression

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB- (Non-investment)	Investment	All
NumOb	1483.47	1360.48	1258.76	1209.39	1367.57	1287.38
Panel A						
Coefficients						
Constant	0.0002***	0.0002***	0.0007***	0.0026**	0.0004***	0.0010***
	(7.7172)	(4.5011)	(3.7094)	(1.8152)	(4.4489)	(2.6107)
Leverage	0.0001	0.0120***	0.0144***	0.0593***	0.0123***	0.0247***
	(0.0128)	(5.8902)	(7.9781)	(4.5847)	(9.3744)	(6.5500)
VIX	0.0011***	0.0024***	0.0036***	0.0178***	0.0029***	0.0069***
	(6.0077)	(8.3151)	(9.9947)	(4.6740)	(12.7306)	(6.2442)
10-year yield	-0.0198***	-0.0399***	-0.0702***	-0.1384**	-0.0547***	-0.0769***
	(-9.0420)	(-6.3843)	(-12.4112)	(-1.9970)	(-13.4347)	(-4.1282)
Gamma	0.0021*	0.0059***	0.0211***	0.0581**	0.0139***	0.0256***
	(1.7287)	(2.8469)	(2.4721)	(2.0240)	(2.9250)	(3.0416)
AdjR^2	0.0365	0.0716	0.0848	0.0697	0.0759	0.0742
Panel B: controlling variables						
Coefficients						
Constant	0.0002***	0.0002***	0.0006***	0.0026**	0.0004***	0.0010***
	(6.6338)	(3.9384)	(3.3077)	(1.7013)	(3.9441)	(2.3866)
Leverage	0.0010	0.0118***	0.0141***	0.0577***	0.0121***	0.0242***
	(0.2218)	(4.7756)	(7.7725)	(4.9146)	(8.5818)	(6.8973)
VIX	0.0012***	0.0026***	0.0032***	0.0139***	0.0028***	0.0057***
	(6.7059)	(8.0878)	(7.6483)	(3.0473)	(10.7825)	(4.5638)
10-year yield	-0.0926***	-0.1670***	-0.1635***	-0.2706	-0.159***	-0.1884**
	(-5.0564)	(-4.2578)	(-4.2130)	(-0.7390)	(-6.1861)	(-1.9189)
Jump	0.0152	-0.0174	0.0224	-0.0311	0.0071	-0.0030
	(1.2841)	(-1.2826)	(1.1394)	(-0.2228)	(0.5903)	(-0.0804)
Gamma	0.0022**	0.0055***	0.0218***	0.0586**	0.0141***	0.0258***
	(1.8638)	(2.6464)	(2.5206)	(1.9964)	(2.9319)	(3.0128)
S&P 500 return	0.0003	0.0009*	-0.0006	-0.0058	0.0000	-0.0015
	(0.7386)	(1.5578)	(-1.0998)	(-0.6818)	(0.0761)	(-0.6707)
10-year yield square	0.0091***	0.0161***	0.0121***	0.0213	0.0134***	0.0155*
	(3.9893)	(3.6138)	(2.5150)	(0.5214)	(4.3001)	(1.4075)
Yield spread	0.0152**	0.0174***	0.0439***	0.0526***	0.0316***	0.0372*
	(1.8204)	(2.8853)	(7.3383)	(4.3017)	(7.6921)	(1.3024)
AdjR^2	0.0424	0.0765	0.0889	0.0759	0.0804	0.0792

Note: NumOb represents the average number of observations. Panel A reports the coefficients and summary statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta \mathrm{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta \mathrm{VOL}_t + \beta_4 \Delta \mathrm{L}_t + \varepsilon_t$, and panel B is for regression $\Delta S_t = \beta_0 + \beta_1 \Delta \mathrm{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta \mathrm{VOL}_t + \beta_4 \Delta \mathrm{L}_t + \beta_5 \Delta r_t^2 + \beta_6 \Delta \mathrm{slope}_t + \beta_7 \Delta \mathrm{S\&P}_t + \beta_8 \Delta \mathrm{jump}_t + \varepsilon_t$. Where β_0 is an intercept, ΔS_t, $\Delta \mathrm{LEV}_t$, Δr_t, $\Delta \mathrm{VOL}_t$, $\Delta \mathrm{L}_t$, r_t^2, slope_t, $\Delta \mathrm{S\&P}_t$, jump_t represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, the difference between the long-term (10-year) and short-term (2-year) risk-free rate; the return of the

S&P 500 and the proxy for jumps in firm value, respectively, at *t*. Explanatory variables in the first column of panel A are the change in the leverage ratio, VIX, 10-year Treasury yield, and γ; and in panel B are the change in the leverage ratio, VIX, 10-year treasury yield, jump of issuing firm's value, γ, S&P 500 index return, square of 10-year yield and spread between 10-year and 2-year yield. The reported coefficients are averages using all entities in a given rating class. The t-statistics in brackets are computed based on the method in Collin-Dufresne et al. (2001). "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row of each panel reports the adjusted R^2.

B5.2 Dummy-variable pooling regression results

The financial crisis provides a unique opportunity to investigate whether the determinants of the changes in CDS spreads are regime dependent. Since the CDS market has performed quite differently before and after the beginning of crisis, it is a concern whether these determinants, especially the liquidity determinant, are time-varying and are consistently significant. For example, Acharya and Pedersen (2005) note that liquidity risk is more pronounced for less liquid securities and in illiquid periods.

I first test the effects of the crisis on determinants by running regression (3), with crisis=1 for the sample from December, 2007 to June, 2009, the recession periods indicated by the National Bureau of Economic Research (NBER), and zero otherwise[15]. Table 5 reports the estimates and associated partial F-statistics for each rating class and the whole sample. There are several important findings. First, the crisis dummy variable is strongly significant at 1% significance level for all pooling samples, suggesting that the intercept of ΔS shifts during a crisis; second, the leverage ratio, VIX, 10-year yield and γ all

[15] I choose to use NBER recession periods because there is no clear definition of when the crisis starts and ends.

remain statistically significant, indicating their importance to explain CDS spreads regardless of the crisis; third, the interaction terms are strongly significant when the whole sample is used, demonstrating that the four determinants are indeed time-varying, the sensitivities of CDS spreads on these determinants change pronouncedly during the crisis; fourth, among the interaction terms, the term with γ is the only one being significant for all rating classes, suggesting the universal shock of liquidity on CDS spreads when a crisis occurs.

Given the finding that the determinants are time-varying caused by crisis, I run regression (4) to further examine how the slope coefficients of the determinants change across credit ratings. Specifically, I test the effect of credit rating on the time-varying determinants during crisis and out of crisis, for instance, testing the interaction effect of credit rating on γ is equivalent to test the hypothesis $\delta_{41} = \delta_{42} = \delta_{43} = 0$.

Table 6 reports the results. Interestingly, the credit rating dummy variable is strongly significant both in and out of crisis, showing that each credit rating class has different ΔS level. Moreover, the interaction terms with the leverage ratio, VIX, and 10-year yield are significant for both sample periods, while the interaction term with γ becomes insignificant during crisis, which suggests that although the shock of liquidity on the change of different rated CDS spreads differs significantly when the CDS market is ‘normal’, it may not be so divergent during crisis. This finding is consistent with the result in Table 4 that the liquidity shock is universal during the crisis.

Table 5. Pooling Regression with Crisis as a Dummy Variable

	AA- ~ AAA		A- ~ A+		BBB- ~ BBB+		Below BBB- (Non-investment)		Investment		All	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	0.0000		-0.0001		0.0000		-0.0019		0.0000		-0.0003	
Leverage	0.0032***	0.0002	0.0098***	0.0000	0.0126***	0.0000	0.0483***	0.0000	0.0115***	0.0000	0.0279***	0.0000
VIX	0.0006***	0.0000	0.0012***	0.0000	0.0031***	0.0000	0.0107***	0.0000	0.0021***	0.0000	0.0038***	0.0000
10-year yield	-0.0138***	0.0000	-0.0286***	0.0000	-0.0583***	0.0000	-0.2434***	0.0000	-0.0426***	0.0000	-0.0858***	0.0000
Gamma	0.0012***	0.0003	0.0015***	0.0000	0.0042***	0.0000	0.0368***	0.0000	0.0029***	0.0000	0.0091***	0.0000
Crisis	0.0006***	0.0063	0.0006***	0.0022	0.0012***	0.0000	0.0132***	0.0000	0.0008***	0.0000	0.0023***	0.0000
Leverage*Crisis	-0.0017	0.1745	0.0001	0.8480	0.0007	0.2473	-0.0122***	0.0000	0.0010**	0.0112	-0.0044***	0.0000
VIX*Crisis	0.0005***	0.0003	0.0008***	0.0000	-0.0001	0.3771	0.0005	0.6822	0.0002**	0.0313	-0.0006***	0.0035
10-year yield*Crisis	-0.0057*	0.0578	-0.0049	0.1041	-0.0014	0.7300	0.0441	0.1583	-0.0029	0.2202	0.0221***	0.0000
Gamma*Crisis	0.0019*	0.0893	0.0022**	0.0446	0.0032**	0.0284	-0.0232**	0.0388	0.0024***	0.0056	-0.0054***	0.0031
AdjR^2	0.0321		0.0635		0.0776		0.0370		0.0689		0.0491	

Note: Coefficients and associated partial F-test statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta r_t + \beta_2 \Delta \mathrm{VOL}_t + \beta_3 \Delta \mathrm{LEV}_t + \beta_4 \Delta \mathrm{L}_t + \delta_0 C + \delta_1 \Delta r_t C + \delta_2 \Delta \mathrm{VOL}_t C + \delta_3 \Delta \mathrm{LEV}_t C + \delta_4 \Delta \mathrm{L}_t C + \varepsilon_t$. Where β_0 is an intercept, ΔS_t, $\Delta \mathrm{LEV}_t$, Δr_t, $\Delta \mathrm{VOL}_t$, $\Delta \mathrm{L}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. C is a dummy variable for crisis, with C=1 for sample dates during the crisis, and C=0 otherwise. Explanatory variables in the first column are the change in the leverage ratio, VIX, 10-year treasury yield, γ, crisis dummy, its interaction with the leverage ratio, VIX, 10-year treasury yield and γ. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

Table 6. Pooling Regression with Credit Rating as a Dummy Variable

	Crisis period		Normal period	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	0.0118		-0.0017	
Leverage	0.0322***	0.0000	0.0274***	0.0000
VIX	0.0104***	0.0000	0.0098***	0.0000
10-year yield	-0.1681***	0.0000	-0.1488***	0.0000
Gamma	0.0022***	0.0024	0.0151***	0.0000
AA	-0.0110***	0.0000	0.0016***	0.0000
A	-0.0111		0.0015	
BBB	-0.0103		0.0017	
Leverage*AA	-0.0280***	0.0001	-0.0244***	0.0000
Leverage*A	-0.0088		-0.0147	
Leverage*BBB	-0.0068		-0.0132	
VIX*AA	-0.0093***	0.0000	-0.0092***	0.0000
VIX*A	-0.0083		-0.0086	
VIX*BBB	-0.0075		-0.0067	
10-year yield*AA	0.1420***	0.0000	0.1355***	0.0000
10-year yield*A	0.1223		0.1184	
10-year yield*BBB	0.1059		0.0836	
Gamma*AA	0.0000	0.3822	-0.0138***	0.0000
Gamma*A	0.0130		-0.0131	
Gamma*BBB	0.0068		-0.0095	
$AdjR^2$	0.0434		0.0638	

Note: Coefficients and associated partial F-test statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta r_t + \beta_2 \Delta \mathrm{VOL}_t + \beta_3 \Delta \mathrm{LEV}_t + \beta_4 \Delta \mathrm{L}_t + \delta_{01} R_1 + \delta_{02} R_2 + \delta_{03} R_3 + \delta_{11} \Delta r_t R_1 + \delta_{12} \Delta r_t R_2 + \delta_{13} \Delta r_t R_3 + \delta_{21} \Delta \mathrm{VOL}_t R_1 + \delta_{22} \Delta \mathrm{VOL}_t R_2 + \delta_{23} \Delta \mathrm{VOL}_t R_3 + \delta_{31} \Delta \mathrm{LEV}_t R_1 + \delta_{32} \Delta \mathrm{LEV}_t R_2 + \delta_{33} \Delta \mathrm{LEV}_t R_3 + \delta_{41} \Delta \mathrm{L}_t R_1 + \delta_{42} \Delta \mathrm{L}_t R_2 + \delta_{43} \Delta \mathrm{L}_t R_3 + \varepsilon_t$. Where β_0 is an intercept, ΔS_t, $\Delta \mathrm{LEV}_t$, Δr_t, $\Delta \mathrm{VOL}_t$, $\Delta \mathrm{L}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. R_1, R_2 and R_3 indicating credit rating dummy for credit rating classes: R_1=1 for any AA- ~ AAA rated CDS, R_2=1 for any A- ~ A+ rated CDS, R_3=1 for any BBB- ~ BBB+ rated CDS, and zero otherwise. Explanatory variables in the first column are the change in the leverage ratio, VIX, 10-year treasury yield, γ, credit rating dummy variables, their interaction with the leverage ratio, VIX, 10-year treasury yield and γ. The null hypothesis for the interaction term is the dummy variable does not change the explanatory variable significantly. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

B5.3 Regime dependent determinants

Another method to test the time-varying determinants is via a Markov regime switching model. Hamilton (1989) proposes an approach to model changes in regime and investigates the different behaviour of US GDP growth. Alexander and Kaeck (2008) use a Markov regime switching model for iTraxx Europe CDS indices and conclude that the determinants of CDS spreads are time-varying. Acharya et al. (2012) use a similar methodology to study the exposure of corporate bond returns to liquidity risk; they find the evidence of time-varying liquidity risk and episodes of flight to liquidity.

In this section I employ the same Markov regime switching model for my CDS spreads data in order to answer two questions: first, are the determinants significant in every regime? Second, are the coefficients of determinants between regimes statistically different? If yes, how large are the differences?

Table 7 presents the estimates and associated t-statistics, Panel A is for crisis regime and Panel B is for normal regime. Sigma measures the standard deviation of residuals; it is 6.28 times larger in the crisis regime than that in the normal regime. The value is larger than in Alexander and Kaeck (2008), which may be due to the individual CDS sample I use instead of their CDS index. I summarize the findings as follows:

Table 7. Markov Regime Switching Regression Model for Four Determinants

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB- (Non-investment)	Investment	All
NumOb	1483.47	1360.48	1258.76	1209.39	1367.57	1287.38
Panel A: crisis regime						
Coefficients						
Constant	0.0007	0.0000	0.0015***	0.0083*	0.0009***	0.0028**
	(1.1022)	(0.0591)	(2.8048)	(1.6126)	(2.8611)	(2.0469)
Leverage	0.0015*	0.0079**	0.0113***	0.0618***	0.0092***	0.0231***
	(1.5346)	(2.3660)	(9.3709)	(3.6306)	(6.5096)	(4.7861)
VIX	0.0010***	0.0017***	0.0029***	0.0194**	0.0023***	0.0068***
	(5.4502)	(6.1042)	(5.6435)	(2.3072)	(7.5699)	(2.9967)
10-year yield	-0.0186***	-0.0465***	-0.0736***	-0.2169***	-0.0589***	-0.1007***
	(-6.8125)	(-9.6712)	(-9.3299)	(-5.5067)	(-12.1947)	(-8.5098)
Gamma	0.0024**	0.0008	0.0334**	0.0515	0.0187**	0.0274**
	(2.0926)	(0.4998)	(2.1219)	(1.2563)	(2.1583)	(2.1808)
sigma	0.0168	0.0355	0.0572	0.3498	0.0458	0.1262
Panel B: normal regime						
Coefficients						
Constant	0.0000	-0.0002***	-0.0003***	-0.0001	-0.0002***	-0.0002***
	(1.0751)	(-4.6496)	(-3.0038)	(-0.5607)	(-3.9253)	(-2.5689)
Leverage	0.0014**	0.0022***	0.0035***	0.0193***	0.0028***	0.0072***
	(2.0522)	(3.1525)	(7.0062)	(4.5598)	(7.4410)	(5.8034)
VIX	0.0001**	0.0006***	0.0016***	0.0063***	0.0011***	0.0025***
	(2.0446)	(5.8034)	(6.4225)	(7.6479)	(7.4908)	(8.7633)
10-year yield	-0.0022**	-0.0083***	-0.0204***	-0.0670***	-0.0144***	-0.0283***
	(-2.5495)	(-6.5536)	(-8.4123)	(-5.1468)	(-9.6445)	(-7.2696)
Gamma	0.0027	0.0051**	0.0063**	-0.0093	0.0055***	0.0016
	(0.9385)	(2.1563)	(2.1436)	(-0.9391)	(3.0217)	(0.5431)
sigma	0.0034	0.0065	0.0123	0.0499	0.0094	0.0201

Note: Estimates of a Markov regime switching model (5) for explanatory variables including the change in the leverage ratio, VIX, 10-year yield and γ, $\Delta S_t = \beta_{i,0} + \beta_{i,1}\Delta \mathrm{LEV}_t + \beta_{i,2}\Delta r_t + \beta_{i,3}\Delta \mathrm{VOL}_t + \beta_{i,4}\Delta \mathrm{L}_t + \varepsilon_{i,t}$, where $i \in \{1,2\}$ represents 2 regimes. I allow the intercept, the coefficients estimates for all explanatory variables, and the residual volatility to vary between the two regimes. NumOb represents the average number of observations. Panel A is the results for the crisis regime and Panel B is for the normal regime. The associated t-statistics are shown in brackets. Sigma measures the standard deviation of residuals. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

a) All explanatory variables are statistically significant for both regimes when considering all entities except γ in normal regime. The changes in CDS spreads of AA- ~ AAA entities are not sensitive to the changes in γ in normal regime, when the CDS market is stable, but are strongly sensitive in crisis regime, when the CDS market is turbulent.

b) All signs of significant coefficients are the same as those of normal multivariate regressions in Table 4. A positive change in leverage ratio, VIX, and γ causes a positive change in CDS spread; a negative change in 10-year yield increases CDS spread, and vice versa. The magnitude of coefficients has generally the same trend as in Table 4, as their sizes increase the lower the rating.

c) The sizes of coefficients in a crisis regime are substantially larger than those in normal a regime. Specifically, the estimates of leverage ratio, VIX, 10-year yield, and γ are 3.22, 2.73, 3.56 and 17.07 times larger in crisis regime than in a normal regime. A Welch's t-test[16] is conducted with the null hypothesis that the coefficients are equal in mean between crisis regime and normal regime, and the results are reported in Table 8. The null hypothesis is rejected at 5% significance level for all variables when using the whole sample, indicating their distinct performance between the two regimes. This finding is largely consistent with the pooling regression results in Table 5 that the determinants behave differently during volatile periods.

[16] Welch's t-test instead of normal student t-test is used because the two samples have unequal variance.

Table 8. Testing of Equal Means between Regimes

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB-	All
NumOb	1483.47	1360.48	1258.76	1209.39	1287.38
T-statistics					
Constant	1.0393	0.9064	3.2990***	1.6374*	2.1843**
Leverage	0.1521	1.6831**	5.9526***	2.4237***	3.1952***
VIX	4.6951***	3.6642***	2.2140**	1.5468*	1.8827**
10-year yield	-5.7451***	-7.6872***	-6.4455***	-3.6149***	-5.8140***
Gamma	-0.0918	-1.5173*	1.6952**	1.4414*	1.9984**
P-value					
Constant	0.1581	0.1839	0.0007	0.0533	0.0150
Leverage	0.4402	0.0484	0.0000	0.0090	0.0008
VIX	0.0001	0.0002	0.0142	0.0634	0.0305
10-year yield	0.0000	0.0000	0.0000	0.0003	0.0000
Gamma	0.4639	0.0660	0.0465	0.0770	0.0233

Note: A Welch's t-test for differences in coefficients with the null hypothesis that the coefficients of determinants are equal between the crisis and normal regimes. Welch's t-test defines t-statistics as $= \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2}}}$, where $\bar{X}_i, S_i^2$ and N_i are the sample mean, sample variance, and sample size for regime i, respectively. NumOb represents the average number of observations. The degree of freedom is approximated as $v = \frac{(\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2})^2}{\frac{S_1^4}{N_1^2 \times (N_1 - 1)} + \frac{S_2^4}{N_2^2 \times (N_2 - 1)}}$. “*”, “**”, “***” represent 10%, 5% and 1% significance level, respectively.

Overall, I conclude from both the dummy-variable pooling regression and Markov regime switching model that all four determinants are significant and time-varying. Liquidity especially is an informative determinant of the changes in CDS spreads, and the sensitivity of the change in CDS spreads to liquidity is much stronger in a crisis regime than in a normal regime. The effects of a liquidity shock on CDS spreads differ significantly across rating groups when the CDS market is tranquil but when it is turbulent the effects become similar, regardless of credit rating. In other words, the impact of the liquidity determinant on the movement of the CDS spread for "safe" securities is as strong as that for "dangerous" securities during volatile periods.

B5.4 Discussion

B5.4.1 The BBB- ~ BBB+ group case study

In this section I pick only those CDSs rated as BBB- ~ BBB+ for a case study because during volatile periods they could behave like CDSs on junk bonds, which makes tests more insightful.

Appendix Figure 6 plots the aggregate γ liquidity measure constructed with only BBB- ~ BBB+ rated CDS. Compared with the γ in Figure 3, it has a similar shape but is slightly bigger. Panel A of Appendix Table 27 reports the results for the multiple OLS regression (1) using the newly constructed γ for both the change in CDS spreads and CDS spread levels. All determinants are strongly significant. Panel B presents the results for the pooling regression (3), as expected, the significant crisis dummy variable indicates the shifted slope, and the only significant interaction term with γ suggests the dramatic change of liquidity shock on the BBB- ~ BBB+ rated CDS spreads, due to crisis.

B5.4.2 Can the explanatory variables explain CDS spreads levels?

I have so far tested the determinants of the changes in CDS spreads because I am more interested in the variation of spreads than the spreads themselves although differences are harder to explain than levels due to the presence of noise in the data and, therefore, a regression in differences provides a more stringent test. In order to provide more insight into the performance of my regressors, I repeat all regression tests and report the results on CDS spreads levels from Appendix Table 28 to 30[17]. The 79.39% adjusted R^2 of the multiple OLS regression for the whole sample suggests that those explanatory variables are sufficient to explain the levels of CDS spreads. In addition, the determinants exhibit even stronger time-varying characteristics than for the changes of CDS spreads.

B5.4.3 Is the regime switching model accurate?

It may be a concern that the accuracy of my conclusion from the Markov regime switching model is biased due to model error and so, to relieve this concern, I also regress the averaged filtered probability of being in crisis regime[18] on the St. Louis Federal Reserve's Financial Stress Index (STLFSI) or its one-week lag in order to check whether the latter is able to reflect and predict the former. STLFSI is an index published by the Federal Reserve Bank of St. Louis and is constructed using principal components analysis on 18 weekly data series including interest rates, yield spreads, and other equity,

[17] Accordingly, explanatory variables are levels instead of differences.

[18] The probability of being in crisis regime is calculated as the sum of the product of the transition probability from normal regime to crisis regime with the probability of being in normal regime at time t-1, and the product of the transition probability from crisis regime to crisis regime with the probability of being in crisis regime at time t-1, the sum is then multiplied by the ratio of the density for crisis regime to the conditional density at t. See Appendix A and Hamilton (1994) for details.

bond, and volatility indices[19]. Higher values of the STLFSI indicate a greater degree of financial stress in the economy. I match my results with the reporting date of STLFSI to a weekly frequency, and apply a standard logit transformation $\log\left[\frac{p_{2,t}}{1-p_{2,t}}\right]$ to the averaged filtered probability $p_{2,t}$. Table 9 presents the univariate regression results. The STLFSI or its lag is strongly significant at 1% significance level; its positive coefficient shows that a greater degree of financial stress in the economy leads to a higher probability of being in a volatility regime of the CDS market. The above 63% adjusted R^2, together with the 81.11% correlation between the transformed filtered probability and the stress index, supports the outcome from my regime switching model.

For a better illustration, Figure 4 plots the time series of the averaged filtered probability of being in the volatility regime, highlighted by several major events occurred during the sample periods. The volatility regime successfully picks up those big market movements such as the take-over of Bear Stearns, the bankruptcy of Lehman Brothers and the 2010 Flash Crash. The overall probability during the NBER recession periods is higher than in other periods.

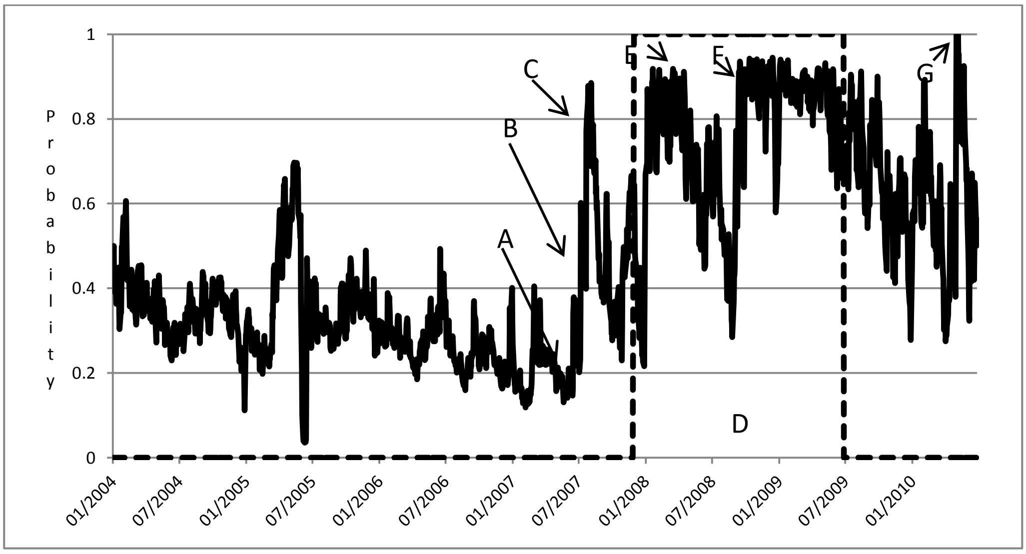
[19] Detailed information regarding the construction of the STLFSI is available online at http://research.stlouisfed.org/publications/net/NETJan2010Appendix.pdf.

Table 9. Univariate Regression of Averaged Probability of Being in Crisis Regime on STLFSI

Coefficients		
Constant	-0.2519***	-0.2481***
	(-6.6560)	(-6.3730)
STFLI(t)	0.6140***	
	(24.8810)	
STFLI(t-1)		0.6056***
		(23.8880)
$AdjR^2$	0.6568	0.6389
Correlation	0.8111	

Note: The coefficients estimates and associated t-statistics for a univariate regression of the logit transformation of the averaged probability of being in the crisis regime on the St. Louis Federal Reserve's Financial Stress Index (STLFSI) or its one-week lag. STLFSI is constructed using principal components analysis on 18 weekly data series including interest rates, yield spreads, and other equity, bond, and volatility indices. Higher values of the STLFSI indicate a greater degree of financial stress in the economy. Adjusted R^2 and the correlation between the transformed probability and the STLFSI value are also shown. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Figure 4. Time Series Plot of Averaged Probability of Volatile Regime



Note: Major events occurred during the sample periods:

A: June 7, 2007. Bear Stearns suspends redemption rights invested in the subprime debt market because of liquidity problems.

B: July 11, 2007. Standard and Poor's places 612 securities backed by subprime residential mortgages on a credit watch.

C: July 31, 2007. Two Bear Sterns hedge funds filed for Chapter 15 bankruptcy.

D: December, 2007 ~ June 2009. Recession periods indicated by the National Bureau of Economic Research (NBER).

E: March, 2008. Bear Stearns was taken over by JPMorgan Chase.

F: September, 2008. The federal government took over Fannie Mae and Freddie Mac, Merrill Lynch was bought by Bank of America and Lehman Brothers filed for bankruptcy.

G: May 6, 2010. United States stock market flash crash happened, the biggest one-day point decline on an intraday basis in Dow Jones Industrial Average history.

B5.4.4 Alternative liquidity proxy

I construct an aggregate liquidity measure for CDS analogous to that of Bao et al. (2011). Researchers have used several other proxies; for example, Bhanot and Guo (2012) use the spread between 3-month Libor and 3-month

Treasury Bill yield (Libor-Tbill); Pu et al. (2011) apply the change in the monthly flow into money market mutual funds, total dollar volume of corporate debt issued, and the difference of the on-the-run and off-the-run Treasury Bond yield. To match my daily frequency CDS data, I test an alternative liquidity proxy as the 3-month Libor-Tbill spread and run the same regressions. I report the main regression results in Table 10 ~ 14. My findings remain consistent, and the liquidity determinant has an even stronger time-varying pattern.

Table 10. Multivariate Regression Using Determinants with Alternative Liquidity Proxy

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB-	All
NumOb	1483.47	1360.48	1258.76	1209.39	1287.38
Panel A					
Coefficients					
Constant	0.0002***	0.0002***	0.0007***	0.0028**	0.0011***
Leverage	0.0002	0.0124***	0.0145***	0.0596***	0.0250***
VIX	0.0010***	0.0022***	0.0034***	0.0174***	0.0066***
10-year yield	-0.0191***	-0.038***	-0.0669***	-0.1393**	-0.0751***
Libor-Tbill	0.0060***	0.0218***	0.0314***	0.1403***	0.0560***
t-statistics					
Constant	8.0710	5.1467	3.8178	1.9086	2.7114
Leverage	0.0513	6.1432	7.8854	4.3968	6.3560
VIX	5.7605	8.3765	9.6381	4.5169	5.9828
10-year yield	-8.2589	-6.3878	-11.9878	-1.9796	-3.9744
Libor-Tbill	3.2320	5.1977	7.6541	4.0230	5.6338
$AdjR^2$	0.0356	0.0726	0.0858	0.0696	0.0748
Panel B: controlling variables					
Coefficients					
Constant	0.0002***	0.0002***	0.0007***	0.0030**	0.0011***
Leverage	0.0011	0.0119***	0.0141***	0.0588***	0.0245***
VIX	0.0011***	0.0025***	0.0030***	0.0134***	0.0055***
10-year yield	-0.0910***	-0.159***	-0.1547***	-0.2482	-0.1769**
Jump	0.0152	-0.0165	0.0248	-0.0364	-0.0032
Libor-Tbill	0.0053***	0.0226***	0.0296***	0.1445***	0.0566***
S&P 500 return	0.0003	0.0008*	-0.0007	-0.0061	-0.0017
10-year yield square	0.0091***	0.0161***	0.0121***	0.0233	0.0160*
Yield spread	0.0113	0.0010	0.0219***	-0.0637***	-0.0071
t-statistics					
Constant	7.1526	4.8751	3.6493	1.9218	2.6490
Leverage	0.2422	4.8407	7.6436	4.7907	6.7302
VIX	6.6016	7.9194	7.4585	2.9911	4.4707
10-year yield	-4.9744	-4.1857	-4.2117	-0.7264	-1.9296
Jump	1.2979	-1.2370	1.2507	-0.2575	-0.0841
Libor-Tbill	2.8385	6.0998	6.9593	5.0678	6.6765
S&P 500 return	0.7015	1.3819	-1.3678	-0.7262	-0.7503
10-year yield square	3.9969	3.6485	2.6072	0.6128	1.5556
Yield spread	1.2915	0.1606	3.5730	-5.1896	-0.2460
$AdjR^2$	0.0412	0.0768	0.0892	0.0771	0.0796

Note: NumOb represents the average number of observations. Panel A reports the coefficients and summary statistics for the regression (1), and panel B is for regression (2). Explanatory variables in the first column of panel A are the change in the leverage ratio, VIX, 10-year Treasury yield, and Libor-Tbill spread; and in panel B are the change in the leverage ratio, VIX, 10-year

Treasury yield, jump of issuing firm's value, Libor-Tbill spread, S&P 500 index return, square of 10-year yield and spread between 10-year and 2-year yield. The reported coefficients are averages using all entities in a given rating class. The t-statistics are computed based on the method in Collin-Dufresne et al. (2001). "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row of each panel reports the adjusted R^2.

Table 11. Pooling Regression with Crisis as a Dummy Variable with Alternative Liquidity Proxy

	AA- ~ AAA		A- ~ A+		BBB- ~ BBB+		Below BBB-		All	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	-0.0001		-0.0002		0.0000		-0.0023		-0.0004	
Leverage	0.0032***	0.0001	0.0098***	0.0000	0.0126***	0.0000	0.0484***	0.0000	0.0279***	0.0000
VIX	0.0006***	0.0000	0.0012***	0.0000	0.0031***	0.0000	0.0105***	0.0000	0.0038***	0.0000
10-year yield	-0.0135***	0.0000	-0.0281***	0.0000	-0.0554***	0.0000	-0.2226***	0.0000	-0.0800***	0.0000
Libor-Tbill	0.0013***	0.0000	0.0024***	0.0000	0.0141***	0.0000	0.0917***	0.0000	0.0273***	0.0000
Crisis	0.0007***	0.0021	0.0008***	0.0002	0.0015***	0.0000	0.0143***	0.0000	0.0026***	0.0000
Leverage*Crisis	-0.0015	0.2192	0.0003	0.6365	0.0010*	0.0624	-0.0122***	0.0000	-0.0042***	0.0000
VIX*Crisis	0.0004***	0.0025	0.0006***	0.0000	-0.0005***	0.0037	-0.0005	0.6577	-0.0010***	0.0000
10-year yield*Crisis	-0.0058*	0.0541	-0.0033	0.2655	-0.0016	0.6982	0.0383	0.2222	0.0213***	0.0000
Libor-Tbill*Crisis	0.0075***	0.0015	0.0219***	0.0000	0.0241***	0.0000	0.0523**	0.0242	0.0206***	0.0000
AdjR^2	0.0331		0.0663		0.0806		0.0383		0.0505	

Note: Coefficients and associated partial F-test statistics for the regression (3). Explanatory variables in the first column are the change in the leverage ratio, VIX, 10-year Treasury yield, Libor-Tbill spread, crisis dummy, its interaction with the leverage ratio, VIX, 10-year treasury yield and Libor-Tbill. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

Table 12. Pooling Regression with Credit Rating as a Dummy Variable with Alternative Liquidity Proxy

	Crisis period		Normal period	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	0.0123		-0.0019	
Leverage	0.0322***	0.0000	0.0274***	0.0000
VIX	0.0093***	0.0000	0.0097***	0.0000
10-year yield	-0.1516***	0.0000	-0.1357***	0.0000
Libor-Tbill	0.1284***	0.0000	0.0622***	0.0000
AA	-0.0114***	0.0000	0.0018***	0.0000
A	-0.0112		0.0017	
BBB	-0.0105		0.0018	
Leverage*AA	-0.0278***	0.0003	-0.0244***	0.0000
Leverage*A	-0.0083		-0.0146	
Leverage*BBB	-0.0062		-0.0132	
VIX*AA	-0.0083***	0.0000	-0.0091***	0.0000
VIX*A	-0.0075		-0.0084	
VIX*BBB	-0.0069		-0.0066	
10-year yield*AA	0.1258***	0.0000	0.1225***	0.0000
10-year yield*A	0.1050		0.1058	
10-year yield*BBB	0.0924		0.0734	
Libor-Tbill*AA	-0.1196	0.0000	-0.0618***	0.0000
Libor-Tbill*A	-0.0958		-0.0604	
Libor-Tbill*BBB	-0.0804		-0.0493	
AdjR^2	0.0456		0.0647	

Note: Coefficients and associated partial F-test statistics for the regression (4). Explanatory variables in the first column are the change in the leverage ratio, VIX, 10-year Treasury yield, Libor-Tbill spread, credit rating dummy variables, their interaction with the leverage ratio, VIX, 10-year Treasury yield and Libor-Tbill spread. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

Table 13. Markov Regime Switching Regression Model for Four Determinants with Alternative Liquidity Proxy

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB-	All
NumOb	1483.47	1360.48	1258.76	1209.39	1287.38
Panel A: crisis regime					
Coefficients					
Constant	0.0003	-0.0001	0.0019***	0.0116*	0.0038**
Leverage	0.0004	0.0154***	0.0124***	0.0648***	0.0263***
VIX	0.0014*	0.0018***	0.0034***	0.0113***	0.0049***
10-year yield	-0.0203***	-0.0417***	-0.0662***	-0.2099***	-0.0947***
Libor-Tbill	0.0272***	0.0270***	0.0409***	0.1867***	0.0748***
sigma	0.0844	0.0535	0.0589	0.3551	0.1373
t-statistics					
Constant	0.5449	-0.2123	2.7002	1.7466	2.1178
Leverage	0.1332	6.6769	9.8220	3.8064	5.4963
VIX	1.7626	3.2073	8.1491	5.0491	7.2414
10-year yield	-2.2672	-5.4404	-5.9947	-4.4095	-6.6733
Libor-Tbill	3.6569	4.0902	5.5229	4.6349	6.2528
Panel B: normal regime					
Coefficients					
Constant	0.0001	-0.0004***	-0.0003***	-0.0002	-0.0003***
Leverage	0.0005	0.0028***	0.0035***	0.0195***	0.0074***
VIX	0.0001	0.0008***	0.0018***	0.0062***	0.0026***
10-year yield	-0.0067***	-0.0139***	-0.0249***	-0.0642***	-0.0312***
Libor-Tbill	0.0017	0.0047**	0.0068***	0.0373***	0.0140***
sigma	0.0068	0.0087	0.0130	0.0507	0.0214
t-statistics					
Constant	1.0824	-3.4415	-3.3677	-0.9904	-3.6509
Leverage	0.4466	2.6501	6.8286	4.7335	5.9717
VIX	0.6570	5.9280	7.0784	7.6313	9.1948
10-year yield	-2.8229	-6.0370	-7.6028	-5.1110	-8.1085
Libor-Tbill	1.3287	2.2889	3.0846	3.5370	4.5158

Note: Estimates of a Markov regime switching model (5) for explanatory variables including the change in the leverage ratio, VIX, 10-year yield and Libor-Tbill spread, $\Delta S_t = \alpha_i + \beta_{i,1}\Delta \mathrm{LEV}_t + \beta_{i,2}\Delta r_t + \beta_{i,3}\Delta \mathrm{VOL}_t + \beta_{i,4}\Delta \mathrm{LIQ}_t + \varepsilon_{i,t}$, where $i \in \{1,2\}$ represents 2 regimes. NumOb represents the average number of observations. I allow the intercept, the coefficients estimates for all explanatory variables, and the residual volatility to vary between the two regimes. Panel A is the results for crisis regime and Panel B is for normal regime. Sigma measures the standard deviation of residuals. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Table 14. Testing of Equal Means between Regimes with Alternative Liquidity Proxy

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB-	All
NumOb	1483.47	1360.48	1258.76	1209.39	1287.38
Coefficients					
Constant	0.3046	0.4822	3.1332***	1.7781**	2.2681**
Leverage	-0.0565	4.9729***	6.4870***	2.5873***	3.8337***
VIX	1.5856*	1.8177**	3.3020***	2.1415**	3.2068***
10-year yield	-1.4673*	-3.4716***	-3.5822***	-2.9598***	-4.3197***
Libor-Tbill	3.3825***	3.2190***	4.4076***	3.5886***	4.9212***
P-value					
Constant	0.3824	0.3156	0.0011	0.0401	0.0121
Leverage	0.4778	0.0000	0.0000	0.0059	0.0001
VIX	0.0666	0.0366	0.0006	0.0176	0.0007
10-year yield	0.0809	0.0004	0.0003	0.0021	0.0000
Libor-Tbill	0.0021	0.0009	0.0000	0.0003	0.0000

Note: A Welch's t-test for differences in coefficients with the null hypothesis that the coefficients of determinants are equal between crisis regime and normal regime. Associated p-value is given. Welch's t-test defines t-statistics as $= \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2}}}$, where $\bar{X}_i, S_i^2$ and N_i are the sample mean, sample variance, and sample size for regime i, respectively. NumOb represents the average number of observations. The degree of freedom is approximated as $v = \frac{(\frac{S_1^2}{N_1} + \frac{S_2^2}{N_2})^2}{\frac{S_1^4}{N_1^2 \times (N_1 - 1)} + \frac{S_2^4}{N_2^2 \times (N_2 - 1)}}$. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

B5.4.5 Alternative risk-free rate proxy

Analogous to Collin-Dufresne et al. (2001) and Ericsson et al. (2009), I approximate risk-free rate with the 10-year Treasury yield. As the CDS contracts are for five years, another appropriate risk-free rate would be 5-year Treasury rate or 5-year swap rate. Blanco, et al. (2005) and Zhu (2006) show that CDS markets use swap rates instead of Treasury rates. Longstaff et al. (2005) reach similar conclusions by representing the risk-free rate with the Treasury, Refcorp, and swap rates.

In this section I conduct a robustness test by using the 5-year Treasury rate and 5-year swap rate and obtain similar results. Indeed, as shown in Table 15, the rates are highly correlated in my sample periods. I present my core tables for the 5-year swap rates in Table 16 ~ 18. The results are very similar to the case for the 10-year Treasury rate, and do not change my conclusion. I further find my model performance becomes improved with a larger adjusted R^2 when using the 5-year swap rates for the risk-free rate.

Table 15. Correlation Matrix of Proxies for Risk-free Rates

Correlation	5-year swap	5-year Treasury	10-year Treasury
5-year swap	1.0000	0.9793	0.9275
5-year Treasury	0.9275	0.9570	1.0000
10-year Treasury	0.9793	1.0000	0.9570

Note: sample correlation matrix from January, 2004 to June, 2010.

Table 16. Multivariate OLS Regression with Alternative Risk-free Rate Proxy

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB- (Non-investment)	Investment	All
NumOb	1483.47	1360.48	1258.76	1209.39	1367.57	1287.38
Panel A						
Coefficients						
Constant	0.0002***	0.0002***	0.0006***	0.0024**	0.0004***	0.0009***
	(7.7130)	(4.0796)	(3.4371)	(1.6203)	(4.0738)	(2.3512)
Leverage	0.0004	0.0122***	0.0147***	0.0596***	0.0125***	0.0250***
	(0.0967)	(5.9646)	(8.1522)	(4.6574)	(9.5872)	(6.6692)
VIX	0.0011***	0.0025***	0.0038***	0.0179***	0.0031***	0.0070***
	(6.2221)	(8.5710)	(10.2761)	(4.7989)	(13.0335)	(6.4881)
5-year swap	-0.0209***	-0.0436***	-0.0690***	-0.1940***	-0.0556***	-0.0922***
	(-10.1342)	(-9.6649)	(-12.4579)	(-3.9101)	(-15.2284)	(-6.6374)
Gamma	0.0020*	0.0057***	0.0211***	0.0551**	0.0138***	0.0247***
	(1.6298)	(2.7259)	(2.4481)	(1.9655)	(2.8771)	(2.9924)
$AdjR^2$	0.0389	0.0743	0.0869	0.0716	0.0782	0.0765
Panel B: controlling variables						
Coefficients						
Constant	0.0002***	0.0001***	0.0006***	0.0025**	0.0004***	0.0009***
	(6.5773)	(3.4356)	(3.1884)	(1.6718)	(3.7355)	(2.3192)
Leverage	0.0012	0.0118***	0.0141***	0.0570***	0.0122***	0.0240***
	(0.2917)	(4.8014)	(7.8452)	(4.8276)	(8.6833)	(6.8477)
VIX	0.0012***	0.0026***	0.0031***	0.0139***	0.0028***	0.0057***
	(6.8475)	(8.1232)	(7.4461)	(3.0517)	(10.6296)	(4.5486)
5-year swap	-0.0430***	-0.0875***	-0.0287***	0.0437	-0.0517**	-0.0265
	(-6.0666)	(-4.4576)	(-0.6349)	0.2020	(-2.0103)	(-0.4408)
Jump	0.0137	-0.0218	0.0156	-0.0578	0.0016	-0.0141
	(1.1863)	(-1.6185)	(0.8075)	(-0.4242)	(0.1372)	(-0.3822)
Gamma	0.0021**	0.0054***	0.0225***	0.0547**	0.0144***	0.0250***
	(1.7624)	(2.5896)	(2.6103)	(1.9563)	(3.0085)	(3.0451)
S&P 500 return	0.0002	0.0006	-0.0009*	-0.0067	-0.0002	-0.0020
	(0.4931)	(1.2418)	(-1.7353)	(-0.7971)	(-0.6923)	(-0.8728)
5-year swap square	0.0023***	0.0049***	-0.0056	-0.0273	-0.0010	-0.0080
	(2.6956)	(2.3739)	(-1.1781)	(-1.4088)	(-0.3824)	(-1.4452)
Yield spread	0.0100	0.0133***	0.0352***	-0.0155	0.0250***	0.0143
	(1.1273)	(2.2323)	(5.8173)	(-1.2761)	(6.0119)	(0.5558)
$AdjR^2$	0.0422	0.0780	0.0910	0.0772	0.0820	0.0808

Note: NumOb represents the average number of observations. Panel A reports the coefficients and summary statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta \text{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta \text{VOL}_t + \beta_4 \Delta \text{L}_t + \varepsilon_t$, and panel B is for regression $\Delta S_t = \beta_0 + \beta_1 \Delta \text{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta \text{VOL}_t + \beta_4 \Delta \text{L}_t + \beta_5 \Delta r_t^2 + \beta_6 \Delta \text{slope}_t + \beta_7 \Delta \text{S\&P}_t + \beta_8 \Delta \text{jump}_t + \varepsilon_t$. Where β_0 is an intercept,ΔS_t, ΔLEV_t, Δr_t, ΔVOL_t, ΔL_t, r_t^2, slope_t, $\Delta \text{S\&P}_t$, jump_t represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, the difference between the long-term (10-year) and short-term (2-year) risk-free rate; the return of the S&P 500 and the proxy for jumps in firm value, respectively, at t. Explanatory variables in the first column of panel A are the change in the leverage ratio, VIX, 5-year swap rate, andγ; and in panel B are the change in the leverage ratio, VIX, 5-year swap rate, jump of issuing firm's value, γ, S&P 500 index return, square of 10-year yield and spread between 10-year and 2-year yield. The reported coefficients are averages using all entities in a given rating class. The t-statistics in brackets are computed based on the method in Collin-Dufresne et al. (2001). "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row of each panel reports the adjusted R^2.

Table 17. Pooling Regression with Crisis as a Dummy Variable and Alternative Risk-free Rate Proxy

	AA- ~ AAA		A- ~ A+		BBB- ~ BBB+		Below BBB- (Non-investment)		Investment		All	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	0.0000		-0.0001		0.0000		-0.0020		0.0000		-0.0003	
Leverage	0.0031***	0.0001	0.0097***	0.0000	0.0125***	0.0000	0.0482***	0.0000	0.0114***	0.0000	0.0279***	0.0000
VIX	0.0006***	0.0000	0.0013***	0.0000	0.0033***	0.0000	0.0113***	0.0000	0.0022***	0.0000	0.0040***	0.0000
5-year swap	-0.0147***	0.0000	-0.0357***	0.0000	-0.0655***	0.0000	-0.2794***	0.0000	-0.0487***	0.0000	-0.0970***	0.0000
Gamma	0.0009***	0.0003	0.0010***	0.0000	0.0032***	0.0000	0.0326***	0.0000	0.0022***	0.0000	0.0076***	0.0000
Crisis	0.0005**	0.0132	0.0005***	0.0088	0.0011***	0.0001	0.0127***	0.0000	0.0007***	0.0000	0.0021***	0.0000
Leverage*Crisis	-0.0013	0.2750	0.0004	0.5169	0.0009*	0.0990	-0.0115***	0.0000	0.0013***	0.0011	-0.0043***	0.0000
VIX*Crisis	0.0004***	0.0003	0.0008***	0.0000	-0.0001	0.3709	0.0004	0.7672	0.0002**	0.0341	-0.0007***	0.0004
5-year swap*Crisis	-0.0091***	0.0006	-0.0031	0.2467	0.0046	0.2049	0.0626**	0.0240	-0.0003	0.9017	0.0164***	0.0002
Gamma*Crisis	0.0024**	0.0373	0.0029***	0.0085	0.0045***	0.0021	-0.0180	0.1094	0.0034***	0.0001	-0.0040**	0.0269
AdjR^2	0.0365		0.0673		0.0806		0.0385		0.0721		0.0513	

Note: Coefficients and associated partial F-test statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta r_t + \beta_2 \Delta \mathrm{VOL}_t + \beta_3 \Delta \mathrm{LEV}_t + \beta_4 \Delta \mathrm{L}_t + \delta_0 C + \delta_1 \Delta r_t C + \delta_2 \Delta \mathrm{VOL}_t C + \delta_3 \Delta \mathrm{LEV}_t C + \delta_4 \Delta \mathrm{L}_t C + \varepsilon_t$. Where β_0 is an intercept, ΔS_t, $\Delta \mathrm{LEV}_t$, Δr_t, $\Delta \mathrm{VOL}_t$, $\Delta \mathrm{L}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. C is a dummy variable for crisis, with C=1 for sample dates during the crisis, and C=0 otherwise. Explanatory variables in the first column are the change in the leverage ratio, VIX, 5-year swap rate, γ, crisis dummy, its interaction with the leverage ratio, VIX, 5-year swap rate and γ. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

Table 18. Pooling Regression with Credit Rating as a Dummy Variable and Alternative Risk-free Rate Proxy

	Crisis period		Normal period	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	0.0113		-0.0017	
Leverage	0.0326***	0.0000	0.0273***	0.0000
VIX	0.0107***	0.0000	0.0101***	0.0000
5-year swap	-0.2037***	0.0000	-0.1828***	0.0000
Gamma	0.0027***	0.0013	0.0129***	0.0000
AA	-0.0106***	0.0000	0.0017***	0.0000
A	-0.0107		0.0015	
BBB	-0.0100		0.0017	
Leverage*AA	-0.0280***	0.0001	-0.0244***	0.0000
Leverage*A	-0.0089		-0.0147	
Leverage*BBB	-0.0069		-0.0132	
VIX*AA	-0.0096***	0.0000	-0.0095***	0.0000
VIX*A	-0.0085		-0.0088	
VIX*BBB	-0.0076		-0.0069	
5-year swap*AA	0.1778***	0.0000	0.1676***	0.0000
5-year swap*A	0.1559		0.1438	
5-year swap*BBB	0.1513		0.1115	
Gamma*AA	-0.0003	0.3894	-0.0119***	0.0000
Gamma*A	0.0128		-0.0115	
Gamma*BBB	0.0070		-0.0084	
AdjR^2	0.0448		0.0682	

Note: Coefficients and associated partial F-test statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta r_t + \beta_2 \Delta \mathrm{VOL}_t + \beta_3 \Delta \mathrm{LEV}_t + \beta_4 \Delta \mathrm{L}_t + \delta_{01} R_1 + \delta_{02} R_2 + \delta_{03} R_3 + \delta_{11} \Delta r_t R_1 + \delta_{12} \Delta r_t R_2 + \delta_{13} \Delta r_t R_3 + \delta_{21} \Delta \mathrm{VOL}_t R_1 + \delta_{22} \Delta \mathrm{VOL}_t R_2 + \delta_{23} \Delta \mathrm{VOL}_t R_3 + \delta_{31} \Delta \mathrm{LEV}_t R_1 + \delta_{32} \Delta \mathrm{LEV}_t R_2 + \delta_{33} \Delta \mathrm{LEV}_t R_3 + \delta_{41} \Delta \mathrm{L}_t R_1 + \delta_{42} \Delta \mathrm{L}_t R_2 + \delta_{43} \Delta \mathrm{L}_t R_3 + \varepsilon_t$. Where β_0 is an intercept,ΔS_t, $\Delta \mathrm{LEV}_t$, Δr_t, $\Delta \mathrm{VOL}_t$, $\Delta \mathrm{L}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. R_1, R_2 and R_3 indicating credit rating dummy for credit rating classes: R_1=1 for any AA- ~ AAA rated CDS, R_2=1 for any A- ~ A+ rated CDS, R_3=1 for any BBB- ~ BBB+ rated CDS, and zero otherwise. Explanatory variables in the first column are the change in the leverage ratio, VIX, 5-year swap rate, γ, credit rating dummy variables, their interaction with the leverage ratio, VIX, 5-year swap rate and γ. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

B5.4.6 Alternative volatility proxy

Several researches have used different proxies for volatility in firm default study. For example, Collin-Dufresne et al. (2001) use VIX data; Ericsson et al. (2009) use the individual firm's EWMA (exponentially weighted moving averaged) historical volatility; Zhong et al. (2010) find that the individual firm's implied volatility dominates historical volatility in explaining the time-series variation in CDS spreads. Campbell and Taksler (2003) use standard deviation of stock returns. Balasubramnian and Cyree (2011) find that when VIX and standard deviation of stock returns are used together, the firm-specific volatility is stronger and VIX loses significance.

In this section for a robustness test, I calculate each firm's historical EWMA volatility of stock returns, and use it as a proxy for volatility for all models and report the results in Table 19 ~ 21. The average correlation between the EWMA volatilities and CDS spreads is 72.89%, compared with the 74.71% correlation between the VIX and CDS spreads. Again, my conclusions are robust to the choice of volatility, and I do not find supporting evidence that historical volatility of stock returns outperforms the VIX to explain CDS spreads.

Table 19. Multivariate OLS Regression with Alternative Volatility Proxy

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB- (Non-investment)	Investment	All
NumOb	1483.47	1360.48	1258.76	1209.39	1367.57	1287.38
Panel A						
Coefficients						
Constant	0.0002***	0.0002***	0.0007***	0.0025*	0.0004**	0.0010***
	(7.7384)	(4.5945)	(3.6695)	(1.7558)	(4.3034)	(2.5314)
Leverage	0.0084***	0.0205***	0.0208***	0.0808***	0.0196***	0.0358***
	(5.0973)	(10.3966)	(10.6694)	(4.4714)	(14.9114)	(6.9533)
EWMA vol	0.0003***	0.0009***	0.0006***	0.0025**	0.0007***	0.0012***
	(3.4867)	(3.7308)	(2.9513)	(2.0125)	(4.8029)	(3.3846)
10-year yield	-0.0258***	-0.0516***	-0.0900***	-0.2626***	-0.0703***	-0.1212***
	(-8.4714)	(-7.6728)	(-13.4764)	(-3.8649)	(-14.9075)	(-6.3772)
Gamma	0.0023**	0.0062***	0.0203***	0.0595**	0.0136***	0.0257***
	(1.9590)	(3.0168)	(2.3899)	(2.1050)	(2.8746)	(3.0955)
$AdjR^2$	0.0250	0.0590	0.0717	0.0618	0.0630	0.0627
Panel B: controlling variables						
Coefficients						
Constant	0.0002***	0.0002***	0.0006***	0.0026*	0.0004***	0.0010***
	(6.8972)	(4.6597)	(3.3829)	(1.7321)	(4.0384)	(2.4506)
Leverage	0.0023	0.0119***	0.0143***	0.0582***	0.0124***	0.0245***
	(0.6323)	(4.9878)	(7.9159)	(4.9388)	(9.0208)	(6.9888)
EWMA vol	0.0004***	0.0009***	0.0007***	0.0024**	0.0008***	0.0012***
	(3.4764)	(3.9634)	(3.3979)	(2.0097)	(5.2742)	(3.5656)
10-year yield	-0.0917***	-0.1651***	-0.1629***	-0.2275	-0.1577***	-0.1762*
	(-4.9464)	(-4.1404)	(-4.2295)	(-0.6291)	(-6.1414)	(-1.8170)
Jump	-0.0176*	-0.1008***	-0.0761***	-0.5237***	-0.0803***	-0.1976***
	(-1.5015)	(-5.2945)	(-2.9086)	(-2.4083)	(-5.0255)	(-3.3089)
Gamma	0.0021*	0.0056***	0.0205***	0.0555**	0.0134***	0.0246***
	(1.8634)	(2.8419)	(2.3643)	(1.9523)	(2.7904)	(2.9390)
S&P 500 return	-0.0008***	-0.0016***	-0.0037***	-0.0187***	-0.0027***	-0.0069***
	(-2.2880)	(-3.9736)	(-8.5132)	(-2.7972)	(-9.1276)	(-3.7890)
10-year yield square	0.0089***	0.0158***	0.0119***	0.0147	0.0131***	0.0135
	(3.8659)	(3.4673)	(2.4676)	(0.3663)	(4.1909)	(1.2523)
Yield spread	0.0173***	0.0224***	0.0476***	0.0702***	0.0357***	0.0448*
	(2.2845)	(3.8572)	(8.1060)	(5.8127)	(8.8551)	(1.5919)
$AdjR^2$	0.0385	0.0730	0.0878	0.0761	0.0782	0.0776

Note: NumOb represents the average number of observations. Panel A reports the coefficients and summary statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta \mathrm{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta \mathrm{VOL}_t + \beta_4 \Delta \mathrm{L}_t + \varepsilon_t$, and panel B is for regression $\Delta S_t = \beta_0 + \beta_1 \Delta \mathrm{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta \mathrm{VOL}_t + \beta_4 \Delta \mathrm{L}_t + \beta_5 \Delta r_t^2 + \beta_6 \Delta \mathrm{slope}_t + \beta_7 \Delta \mathrm{S\&P}_t + \beta_8 \Delta \mathrm{jump}_t + \varepsilon_t$. Where β_0 is an intercept,ΔS_t, $\Delta \mathrm{LEV}_t$, Δr_t, $\Delta \mathrm{VOL}_t$, $\Delta \mathrm{L}_t$, r_t^2, slope_t, $\Delta \mathrm{S\&P}_t$, jump_t represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, the difference between the long-term (10-year) and short-term (2-year) risk-free rate; the return of the S&P 500 and the proxy for jumps in firm value, respectively, at *t*. Explanatory variables in the first column of panel A are the change in the leverage ratio, EWMA volatility, 10-year treasury yield, andγ; and in panel B are the change in the leverage ratio, EWMA volatility, 10-year treasury yield, jump of issuing firm's value, γ, S&P 500 index return, square of 10-year yield and spread between 10-year and 2-year yield. The reported coefficients are averages using all entities in a given rating class. The t-statistics in brackets are computed based on the method in Collin-Dufresne et al. (2001). "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row of each panel reports the adjusted R^2.

Table 20. Pooling Regression with Crisis as a Dummy Variable and Alternative Volatility Proxy

	AA- ~ AAA		A- ~ A+		BBB- ~ BBB+		Below BBB- (Non-investment)		Investment		All	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	0.0000		-0.0001		0.0000		-0.0019		0.0000		-0.0003	
Leverage	0.0047***	0.0000	0.0117***	0.0000	0.0159***	0.0000	0.0556***	0.0000	0.0140***	0.0000	0.0315***	0.0000
EWMA vol	0.0003***	0.0058	0.0001***	0.0000	0.0001***	0.0000	0.0001	0.1659	0.0001***	0.0000	0.0000***	0.0000
10-year yield	-0.0160***	0.0000	-0.0337***	0.0000	-0.0723***	0.0000	-0.2920***	0.0000	-0.0516***	0.0000	-0.1026***	0.0000
Gamma	0.0012***	0.0001	0.0017***	0.0000	0.0047***	0.0000	0.0383***	0.0000	0.0032***	0.0000	0.0096***	0.0000
Crisis	0.0005**	0.0196	0.0005**	0.0136	0.0010***	0.0002	0.0126***	0.0000	0.0007***	0.0000	0.0021***	0.0000
Leverage*Crisis	0.0034***	0.0019	0.0041***	0.0000	0.0031***	0.0000	-0.0062**	0.0181	0.0038***	0.0000	-0.0024***	0.0001
EWMA vol*Crisis	-0.0002	0.1356	0.0003***	0.0008	0.0002*	0.0573	0.0004	0.5184	0.0003***	0.0000	0.0008***	0.0000
10-year yield*Crisis	-0.0105***	0.0004	-0.0137***	0.0000	-0.0092**	0.0228	0.0060	0.8451	-0.0108***	0.0000	0.0133***	0.0068
Gamma*Crisis	0.0021*	0.0661	0.0022**	0.0448	0.0020	0.1801	-0.0246**	0.0294	0.0019**	0.0272	-0.0065***	0.0004
AdjR^2	0.0230		0.0533		0.0657		0.0321		0.0592		0.0453	

Note: Coefficients and associated partial F-test statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta r_t + \beta_2 \Delta \mathrm{VOL}_t + \beta_3 \Delta \mathrm{LEV}_t + \beta_4 \Delta \mathrm{L}_t + \delta_0 C + \delta_1 \Delta r_t C + \delta_2 \Delta \mathrm{VOL}_t C + \delta_3 \Delta \mathrm{LEV}_t C + \delta_4 \Delta \mathrm{L}_t C + \varepsilon_t$. Where β_0 is an intercept, ΔS_t, $\Delta \mathrm{LEV}_t$, Δr_t, $\Delta \mathrm{VOL}_t$, $\Delta \mathrm{L}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. C is a dummy variable for crisis, with C=1 for sample dates during the crisis, and C=0 otherwise. Explanatory variables in the first column are the change in the leverage ratio, EWMA volatility, 10-year treasury yield, γ, crisis dummy, its interaction with the leverage ratio, EWMA volatility, 10-year treasury yield and γ. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

Table 21. Pooling Regression with Credit Rating as a Dummy Variable and Alternative Volatility Proxy

	Crisis period		Normal period	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	0.0113		-0.0017	
Leverage	0.0447***	0.0000	0.0342***	0.0000
EWMA vol	-0.0002***	0.0007	0.0000	0.1521
10-year yield	-0.2460***	0.0000	-0.1927***	0.0000
Gamma	0.0029***	0.0054	0.0158***	0.0000
AA	-0.0106***	0.0000	0.0016***	0.0000
A	-0.0108		0.0015	
BBB	-0.0100		0.0017	
Leverage*AA	-0.0332***	0.0000	-0.0297***	0.0000
Leverage*A	-0.0155		-0.0197	
Leverage*BBB	-0.0139		-0.0169	
EWMA vol*AA	0.0009***	0.0000	0.0002	0.5777
EWMA vol*A	0.0023		0.0001	
EWMA vol*BBB	0.0014		0.0002	
10-year yield*AA	0.2112***	0.0000	0.1771***	0.0000
10-year yield*A	0.1831		0.1573	
10-year yield*BBB	0.1604		0.1136	
Gamma*AA	-0.0006	0.4779	-0.0145***	0.0000
Gamma*A	0.0116		-0.0137	
Gamma*BBB	0.0045		-0.0097	
$AdjR^2$	0.0377		0.0526	

Note: Coefficients and associated partial F-test statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta r_t + \beta_2 \Delta \mathrm{VOL}_t + \beta_3 \Delta \mathrm{LEV}_t + \beta_4 \Delta \mathrm{L}_t + \delta_{01} R_1 + \delta_{02} R_2 + \delta_{03} R_3 + \delta_{11} \Delta r_t R_1 + \delta_{12} \Delta r_t R_2 + \delta_{13} \Delta r_t R_3 + \delta_{21} \Delta \mathrm{VOL}_t R_1 + \delta_{22} \Delta \mathrm{VOL}_t R_2 + \delta_{23} \Delta \mathrm{VOL}_t R_3 + \delta_{31} \Delta \mathrm{LEV}_t R_1 + \delta_{32} \Delta \mathrm{LEV}_t R_2 + \delta_{33} \Delta \mathrm{LEV}_t R_3 + \delta_{41} \Delta \mathrm{L}_t R_1 + \delta_{42} \Delta \mathrm{L}_t R_2 + \delta_{43} \Delta \mathrm{L}_t R_3 + \varepsilon_t$. Where β_0 is an intercept, ΔS_t, $\Delta \mathrm{LEV}_t$, Δr_t, $\Delta \mathrm{VOL}_t$, $\Delta \mathrm{L}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. R_1, R_2 and R_3 indicating credit rating dummy for credit rating classes: R_1=1 for any AA- ~ AAA rated CDS, R_2=1 for any A- ~ A+ rated CDS, R_3=1 for any BBB- ~ BBB+ rated CDS, and zero otherwise. Explanatory variables in the first column are the change in the leverage ratio, EWMA volatility, 10-year Treasury yield, γ, credit rating dummy variables, their interaction with the leverage ratio, EWMA volatility, 10-year treasury yield and γ. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

B5.4.7 Are leverage ratios serially correlated?

Define leverage ratio as

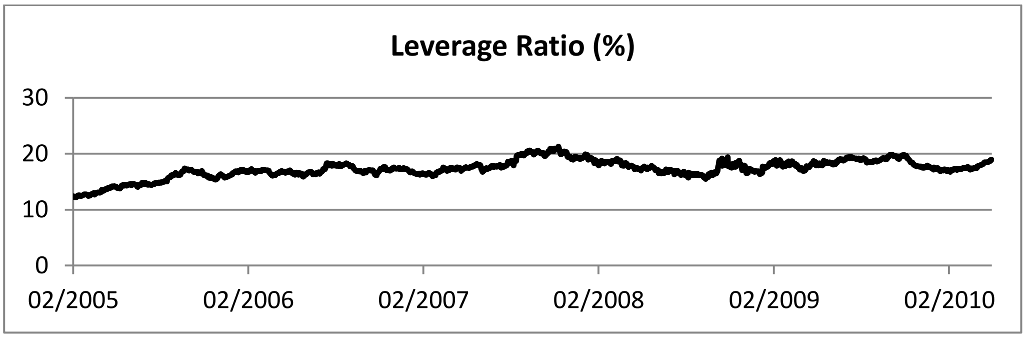
$$\frac{\text{Book value of debt+Book value of preferred equity}}{\text{Market value of equity+ Book value of debt+Book value of preferred equity}}$$

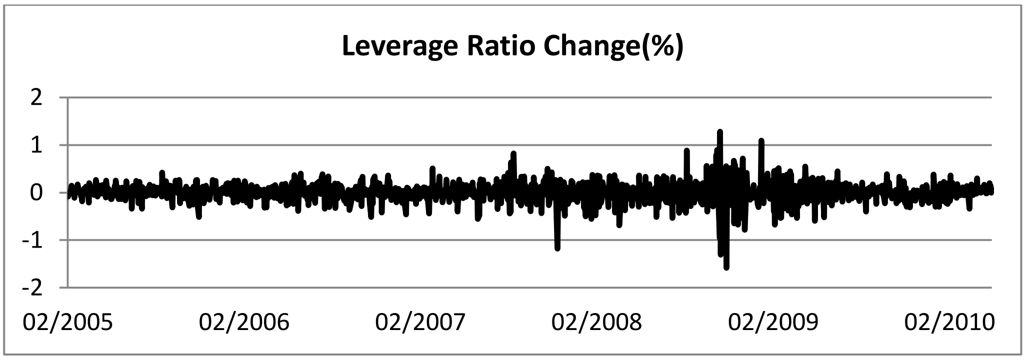
I linearly interpolate quarterly book values of debt and preferred equity in order to estimate daily leverage ratios, as all other variables are at a daily frequency. One concern about the ratio is therefore whether it is serially correlated as the change of a highly auto-correlated variable might lead to a singular problem in regression.

I conjecture that this concern is not serious since, instead of linearly interpolating the leverage ratios, I only interpolate quarterly book values of debt and preferred equity, then estimate daily leverage ratio together with the daily market values of equity. Such approximation allows the daily change of leverage ratio to be varied without suffering strong serial autocorrelation. There are other ways to approximate the leverage ratio, for instance, estimating the market value of debt as the value of all corporate bonds an entity issues. However, not all bonds have trading data on each day. Also, the assumption that corporate bonds represent all debt is restricting; some entities have convertible bonds debt as well, which makes the mark-to-market debt value even more complicated and prone to error. Another way to avoid this issue is to run the regressions only around quarter ends. This way is not feasible in my study due to the data sample size limitation, my whole sample is from January 2004 to June 2010, and many CDSs have shorter sample sizes than that. This means I end up with at most 26 observations for all CDSs, which generates unreliable regression results.

To illustrate how leverage ratio evolves, I randomly select the entity "Wal-Mart Stores, Inc" as an example. Figure 5 plots its daily leverage ratio (%) and its first order difference used for regressions. Obviously, the leverage ratio and its change fluctuate every day. There is no longer strong serial autocorrelation for the change of leverage ratio. For instance, it is -0.1106 for the entity "Wal-Mart Stores, Inc". I randomly select several entities and calculate the autocorrelations for the changes of their leverage ratios; all values remain low, with majority below 0.1. The results for an Augmented Dickey-Fuller (ADF) test for the null that x has a unit root are shown in Table 22: the leverage difference strongly rejects the one unit root hypothesis.

Figure 5. Time Series Plot of Leverage Ratios of Wal-Mart Stores, Inc





Note: time series plot of leverage ratios of a selected CDS reference entity: Wal-Mart Stores, Inc, where leverage ratio is defined as

$$\frac{\text{Book value of debt+Book value of preferred equity}}{\text{Market value of equity+ Book value of debt+Book value of preferred equity}}$$

Table 22. Unit Root Test for Leverage Ratios of Wal-Mart Stores, Inc

	Leverage ratio	Leverage ratio change
Dickey-Fuller	-3.2365*	-10.5615***
P-value	0.08163	0.01

Note: An Augmented Dickey-Fuller (ADF) test for the null that x has a unit root.

B5.4.8 The role of counterparty risk

Pu et al. (2011) look at the system wide counterparty risk together with liquidity risk. A counterparty risk is a type of risk that a counterparty will not pay what it is obligated to do in a contract. For a CDS contract, a counterparty risk can emerge from the failure of the protection buyer to pay CDS spreads, which makes it difficult for the protection seller to manage the risk and results in an increased cost of insuring against default. Stulz (2010) finds that counterparty risk has become an important factor for credit derivatives valuation. Pu et al. (2011) use the spread between three-month Libor and Repo rates as a measure of aggregate counterparty risk. In order to control for counterparty risk, I run the regression below:

$$\Delta S_t = \beta_0 + \beta_1 \Delta \mathrm{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta \mathrm{VOL}_t + \beta_4 \Delta \mathrm{L}_t + \beta_5 \Delta r_t^2 + \beta_6 \Delta \mathrm{slope}_t$$

$$+\beta_7 \Delta \mathrm{S\&P}_t + \beta_8 \Delta \mathrm{jump}_t + \beta_9 \Delta \mathrm{counter}_t + \varepsilon_t$$

where $\Delta \mathrm{counter}_t$ represents the change of counterparty risk. Table 23 reports the results. I find my liquidity measure γ is strongly significant even after controlling for counterparty risk, which suggests that liquidity risk still determines the change of CDS default spreads after excluding possible counterparty risk premium.

Table 23. Multiple Regression Controlling for Counterparty Risk

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB-	All
NumOb	1483.47	1360.48	1258.76	1209.39	1287.38
Coefficients					
Constant	0.0002***	0.0002***	0.0006***	0.0027**	0.001***
Leverage	0.0009	0.0117***	0.0140***	0.0579***	0.024***
VIX	0.0011***	0.0024***	0.0030***	0.0129***	0.005***
10-year yield	-0.0905***	-0.158***	-0.1511***	-0.2176	-0.1668**
Jump	0.0189*	-0.0044	0.0417**	0.0401	0.0273
Gamma	0.0129***	0.043***	0.0544***	0.2398***	0.098***
S&P 500 return	0.0020*	0.005***	0.0208***	0.0542*	0.024***
10-year yield square	0.0002	0.0005	-0.0009*	-0.0075	-0.0022
Yield spread	0.0089***	0.0151*	0.0106	0.0150	0.0129
Libor Repo spread	0.0127*	0.0073	0.0322***	-0.0025	0.0150
t-statistics					
Constant	6.8520	4.2313	3.4821	1.7841	2.5042
Leverage	0.2152	4.7054	7.6637	4.8708	6.8239
VIX	6.4961	7.8264	7.2426	2.8606	4.3096
10-year yield	-4.9706	-4.1652	-3.9676	-0.5959	-1.7059
Jump	1.6504	-0.3353	1.9311	0.2799	0.7023
Gamma	5.1924	8.3735	9.1955	4.3351	6.1891
S&P 500 return	1.7069	2.3068	2.4023	1.8515	2.8167
10-year yield square	0.5180	1.0067	-1.7705	-0.8920	-0.9834
Yield spread	2.4244	1.7640	1.2800	0.1441	1.1786
Libor Repo spread	1.4636	1.1679	5.3772	-0.2010	0.5430
AdjR^2	0.0444	0.0810	0.0930	0.0787	0.0829

Note: coefficients and summary statistics for the regression $\Delta S_t = \beta_0 + \beta_1 \Delta\text{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta\text{VOL}_t + \beta_4 \Delta\text{L}_t + \beta_5 \Delta r_t^2 + \beta_6 \Delta\text{slope}_t + \beta_7 \Delta\text{S\&P}_t + \beta_8 \Delta\text{jump}_t + \beta_9 \Delta\text{counter}_t + \varepsilon_t$, where β_0 is an intercept, ΔS_t, ΔLEV_t, Δr_t, ΔVOL_t, ΔL_t, r_t^2, slope_t, $\Delta\text{S\&P}_t$, jump_t, $\Delta\text{counter}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, the difference between the long-term (10-year) and short-term (2-year) risk-free rate, the return of the S&P 500, the proxy for jumps in firm value and the counterparty risk, respectively, at *t*. Explanatory variables in the first column of are the change in the leverage ratio, VIX, 10-year Treasury yield, jump of issuing firm's value, γ, S&P 500 index return, square of 10-year yield, spread between 10-year and 2-year yield, spread between 3-month Libor and Repo rate. NumOb represents the average number of observations. The reported coefficients are averages using all entities in a given rating class. The t-statistics in brackets are computed based on the method in Collin-Dufresne et al. (2001). "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row of each panel reports the adjusted R^2.

B5.4.9 Liquidity shocks against number of quotes

It is useful to investigate whether my liquidity measure captures the characteristics of liquidity of a CDS contract. One way to gauge the latter is the number of quotes, which reflects how many quotes a CDS contract has had provided by vendors in CDS markets. Intuitively, a CDS is more liquid if there are more vendors willing to provide quotes and it has consequently a larger number of quotes.

Analogous to Liu (2006), I first check whether liquidity is priced in CDS spreads by estimating the liquidity sensitivity β for each CDS as

$$\Delta S_t = \alpha + \beta \Delta \mathrm{L}_t + \varepsilon_t$$

where S_t is the CDS spread, L_t is the aggregate liquidity level at date t. My specification in the above equation implicitly assumes that CDS spread is mainly driven by liquidity and is, therefore, a strong assumption. Nevertheless, it is good for illustrative purposes. Table 24 reports the univariate regression results. The strongly significant coefficients for both investment-grade and non-investment-grade suggest that the aggregate liquidity L is priced in.

Table 24. Univariate Liquidity Shock Regression

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB- (Non-investment)	Investment	All
NumOb	1483.47	1360.48	1258.76	1209.39	1367.57	1287.38
Coefficients						
Constant	0.0002***	0.0003***	0.0008***	0.0032**	0.0006***	0.0013***
	(7.9088)	(5.3943)	(4.2376)	(2.1454)	(5.2351)	(3.0689)
Gamma	0.0032***	0.0112***	0.0299***	0.0884***	0.0207***	0.0386***
	(2.5607)	(4.3960)	(3.2390)	(2.9108)	(4.0088)	(4.2671)
AdjR^2	0.0024	0.0036	0.0040	0.0103	0.0037	0.0054

I then regress CDS liquidity β on the number of quotes to examine their relationship

$$\beta_i = \alpha_0 + \alpha_1 q_i + \varepsilon_i$$

where β_i and q_i are the liquidity sensitivity β and the number of quotes for the i^{th} CDS. The significant negative coefficient for q reported in Table 25 is expected, suggesting that the liquidity sensitivity is smaller for the CDS with larger number of quotes, and vice versa. In other words, the shock of aggregate liquidity on the spreads of a CDS becomes less if it has a larger number of quotes.

Table 25. Liquidity Sensitivity against Number of Quotes

Constant	0.1429***
	(3.4420)
Quotes	-0.0001**
	(-2.5720)
$AdjR^2$	0.0228

Furthermore, I rank all CDSs to four quantiles by the number of quotes, the 1^{st} quantile group has the smallest number of quotes, and the 4^{th} quantile group has the largest number of quotes. Then I estimate the average liquidity β for each group and test the null hypothesis that their liquidity β is equal in mean.

Table 26. Quantile Group Based on Number of Quotes

Quote group	Mean liquidity beta	Equal mean test
1st Quantile	0.0706	2.9664***
4th Quantile	0.0165	

As shown in Table 26, the 1st Quantile group is much more sensitive to the aggregate liquidity shock by having an over four-times bigger liquidity beta than the 4th Quantile group. In addition, the equal mean test is strongly rejected.

All tests above suggest that liquidity sensitivity is larger in my sample for CDS contracts with lower number of quotes, suggesting the good economic sense of my liquidity measure.

Chapter B6. Conclusion

In this study I investigate as determinants of the changes in CDS spreads, firm leverage, volatility, risk-free interest rate and liquidity. By regressing the changes in daily CDS quotes from January, 2004 to June, 2010 on the changes in proxies of these possible determinants, I find that all four are statistically significant and time-varying, robust to the use of different proxies for liquidity under different methodologies: a dummy-variable pooling regression and a regime switching regression model. Among the four determinants, the effects of liquidity shock on CDS spreads differ significantly across rating groups when the CDS market is tranquil but when it is turbulent the effects become similar, regardless of credit rating. In other words, the impact of the liquidity determinant on the movement of the CDS spread for “safe” securities is as strong as that for “dangerous” securities during volatile periods.

Appendix B.A: Hamilton (1989)'s Markov Two-regime Switching Model Estimation

Since Hamilton's (1989) Markov regime switching model is standard, in this section I briefly review the estimation method of a two-regime model - for detail refer to Hamilton (1989) and Hamilton (1994). Assuming a state variable s_t determines which regime it is at time t, and the probability of a transition or a stay in the same regime at time t+1 is only decided by the state at time t. Let the Markov chain be represented by a vector ω with ith element being one if $s_t = i$ and zero otherwise. Since the Markov chain is unobservable, we can only assign a probability of being in each regime. Denote the Markov switching probability as matrix p with elements:

$$p_{11} = \text{Prob}(s_t = 1|s_{t-1} = 1)$$

$$p_{22} = \text{Prob}(s_t = 2|s_{t-1} = 2)$$

So the conditional expectation of ω_{t+1} given all information up to t is calculated as

$$\text{E}(\omega_{t+1}|\omega_t) = p\omega_t.$$

Suppose the Markov regime switching regression equation is

$$y_t = \beta_i x_t + \varepsilon_{i,t}$$

Under the Gaussian assumption of $\varepsilon_{i,t}$, the conditional densities is

$$f(y_t|s_{t=i}, x_t, I_{t-1}; \theta) = \frac{1}{\sqrt{2\pi}\sigma_i}\exp\{-\frac{(y_t - \beta_i x_t)^2}{2\sigma_i^2}\}$$

where $\theta = (p, \beta_i, \sigma_i)$ is a parameter set to be estimated, I_{t-1} is an information set up to time t-1. Multiplying the conditional densities by the conditional expectation of ω_t yields the joint density

$$f(y_t, s_t, s_{t-1} | x_t, I_{t-1}; \theta) = f(y_t | s_{t=i}, x_t, I_{t-1}; \theta) \times \text{Prob}(s_t, s_{t-1})$$

Finally we can apply a maximum log likelihood method to estimate θ under the constraint that probabilities sum to one.

Appendix B.B: Tables

Appendix Table 27. Multiple OLS and Dummy-variable Pooling Regression for BBB- ~ BBB+ Rated CDS

	Difference	Level
Panel A		
Coefficients		
Constant	0.0006***	0.6368***
	(3.8679)	(3.2440)
Leverage	0.0146***	0.0323***
	(8.0600)	(7.5722)
VIX	0.0036***	0.0271***
	(10.0231)	(9.1773)
10-year yield	-0.0705***	-0.2842***
	(-12.4987)	(-8.0528)
Gamma	0.0138***	0.1818**
	(2.3062)	(1.7832)
AdjR^2	0.0836	0.7639
Panel B	Coefficients	Pr(>F)
Constant	0.0000	
Leverage	0.0126***	0.0000
VIX	0.0031***	0.0000
10-year yield	-0.0579***	0.0000
Gamma	-0.0006*	0.0904
Crisis	0.0013***	0.0000
Leverage*Crisis	0.0008	0.1304
VIX*Crisis	-0.0002	0.3431
10-year yield*Crisis	-0.0033	0.4239
Gamma*Crisis	0.0032**	0.0333
AdjR^2	0.0772	

Note: Panel A reports the results for the multiple OLS regression $\Delta S_t = \beta_0 + \beta_1 \Delta\mathrm{LEV}_t + \beta_2 \Delta r_t + \beta_3 \Delta\mathrm{VOL}_t + \beta_4 \Delta\mathrm{L}_t + \varepsilon_t$, where β_0 is an intercept, ΔS_t, $\Delta\mathrm{LEV}_t$, Δr_t, $\Delta\mathrm{VOL}_t$, $\Delta\mathrm{L}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. Column "difference" is for the change of CDS spreads, and column "level" is for the CDS spreads. Explanatory variables in the first column of panel A are the change in the leverage ratio, VIX, 10-year treasury yield, and γ. The associated t-statistics are shown in brackets. Panel B presents the results for the pooling regression $\Delta S_t = \beta_0 + \beta_1 \Delta r_t + \beta_2 \Delta\mathrm{VOL}_t + \beta_3 \Delta\mathrm{LEV}_t + \beta_4 \Delta\mathrm{L}_t + \delta_0 C + \delta_1 \Delta r_t C + \delta_2 \Delta\mathrm{VOL}_t C + \delta_3 \Delta\mathrm{LEV}_t C + \delta_4 \Delta L_t C + \varepsilon_t$. Where β_0 is an intercept, ΔS_t , $\Delta\mathrm{LEV}_t$, Δr_t, $\Delta\mathrm{VOL}_t$, $\Delta\mathrm{L}_t$ represents the change in CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. C is a dummy variable for crisis, with C=1 for sample dates during the crisis, and C=0 otherwise.. Explanatory variables in the first column are the change in the leverage ratio, VIX, 10-year treasury yield, γ, crisis dummy, its interaction with the leverage ratio, VIX, 10-year treasury yield and γ. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Appendix Table 28. Multiple OLS Regression for CDS Spreads Level

	AA- ~ AAA	A- ~ A+	BBB- ~ BBB+	Below BBB- (Non-investment)	Investment	All
NumOb	1484.47	1361.48	1259.76	1210.39	1367.57	1287.38
Panel A						
Coefficients						
Constant	0.5611***	0.5492***	0.7124***	-2.3793	0.6392***	-0.1591
	(13.8977)	(4.1347)	(4.0191)	(-1.0203)	(5.8998)	(-0.2549)
Leverage	0.0109**	0.0222***	0.0330***	0.1715***	0.0272***	0.0653***
	(2.1460)	(4.9310)	(7.4613)	(3.8171)	(9.0460)	(5.1450)
VIX	0.0094***	0.0170***	0.0266***	0.1100***	0.0216***	0.0450***
	(10.3009)	(9.6091)	(9.1374)	(6.2432)	(12.2110)	(8.2893)
10-year yield	-0.1515***	-0.2172***	-0.3018***	-0.8300***	-0.2577***	-0.4091***
	(-20.7386)	(-9.7149)	(-10.0382)	(-5.2263)	(-13.7700)	(-8.7273)
Gamma	0.0054*	0.0033	0.2196**	0.4463***	0.1213**	0.2073***
	(1.6890)	(0.4339)	(1.8082)	(2.8171)	(1.8225)	(3.1928)
AdjR^2	0.8857	0.8175	0.7637	0.7937	0.7939	0.7939
Panel B: controlling variables						
Coefficients						
Constant	0.7050***	0.9236***	1.2435***	1.4807	1.0795***	1.1856***
	(15.9350)	(8.1394)	(6.1626)	(1.0117)	(9.1232)	(3.0039)
Leverage	0.0149***	0.0287***	0.0345***	0.1572***	0.0307***	0.0642***
	(3.5974)	(6.0774)	(7.9699)	(4.3628)	(10.3134)	(6.1902)
VIX	0.0113***	0.0193***	0.0312***	0.1348***	0.0251***	0.0541***
	(11.9827)	(9.5321)	(9.8128)	(5.7655)	(12.8373)	(7.6853)

10-year yield	-0.1598***	-0.2471***	-0.3367***	-1.0050***	-0.2886***	-0.4781***
	(-14.1471)	(-10.5430)	(-9.0330)	(-4.7196)	(-12.8425)	(-7.7327)
Jump	0.5410***	1.1767***	1.6182***	6.5196***	1.3637***	2.7272***
	(7.0404)	(6.1857)	(5.8875)	(3.8601)	(8.1659)	(5.6410)
Gamma	0.0032	-0.0074	0.2134**	0.5152***	0.1138**	0.2200***
	(0.9699)	(-1.3076)	(1.7582)	(2.7386)	(1.7111)	(3.1211)
S&P 500 return	-0.0014***	-0.0013*	-0.0032***	0.0245**	-0.0023***	0.0048*
	(-3.2132)	(-1.3467)	(-2.3892)	(1.9907)	(-2.8742)	(1.4112)
10-year yield square	-0.0088***	-0.0182***	-0.0308***	-0.2025***	-0.0243***	-0.0714***
	(-5.3582)	(-8.4272)	(-6.6620)	(-6.0817)	(-8.9936)	(-6.9313)
Yield spread	-0.0197***	-0.0896***	-0.0706***	-0.6448***	-0.0734***	-0.2245***
	(-2.5260)	(-6.1100)	(-5.0571)	(-46.7730)	(-7.6102)	(-3.4756)
AdjR^2	0.9016	0.8488	0.8017	0.8282	0.8276	0.8277

Note: NumOb represents the average number of observations. Panel A reports the coefficients and summary statistics for the regression $S_t = \beta_0 + \beta_1\text{LEV}_t + \beta_2 r_t + \beta_3\text{VOL}_t + \beta_4\text{L}_t + \varepsilon_t$, and panel B is for regression $S_t = \beta_0 + \beta_1\text{LEV}_t + \beta_2 r_t + \beta_3\text{VOL}_t + \beta_4\text{L}_t + \beta_5 r_t^2 + \beta_6\text{slope}_t + \beta_7\text{S\&P}_t + \beta_8\text{jump}_t + \varepsilon_t$. Where β_0 is an intercept,S_t, LEV_t, r_t, VOL_t, L_t, r_t^2, slope_t, $\Delta\text{S\&P}_t$, jump_t represents the CDS spread, leverage ratio, risk-free rate, volatility and liquidity, the difference between the long-term (10-year) and short-term (2-year) risk-free rate; the return of the S&P 500 and the proxy for jumps in firm value, respectively, at *t*. Explanatory variables in the first column of panel A are the leverage ratio, VIX, 10-year treasury yield, andγ; and in panel B are the leverage ratio, VIX, 10-year Treasury yield, jump of issuing firm's value, γ, S&P 500 index return, square of 10-year yield and spread between 10-year and 2-year yield. The reported coefficients are averages using all entities in a given rating class. The t-statistics shown in brackets are computed based on the method in Collin-Dufresne et al. (2001). "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row of each panel reports the adjusted R^2.

Appendix Table 29. Pooling Regression for CDS Spreads Level with Crisis as a Dummy Variable

	AA- ~ AAA		A- ~ A+		BBB- ~ BBB+		Below BBB- (Non-investment)		Investment		All	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	0.4268		0.4862		0.2297		1.1789		0.260380983		-0.6331	
Leverage	0.0072***	0.0000	0.0098***	0.0000	0.0214***	0.0000	0.0909***	0.0000	0.0196***	0.0000	0.0759***	0.0000
VIX	0.0068***	0.0000	0.0115***	0.0000	0.0195***	0.0000	0.0775***	0.0000	0.0137***	0.0000	0.0288***	0.0000
10-year yield	-0.1008***	0.0000	-0.1200***	0.0000	-0.0923***	0.0000	-0.7022***	0.0000	-0.0916***	0.0000	-0.1443***	0.0000
Gamma	0.0124***	0.0000	0.0259***	0.0000	0.0302***	0.0000	0.1628***	0.0000	0.0267***	0.0000	0.0317**	0.0465
Crisis	0.3749***	0.0000	0.7974***	0.0000	1.1920***	0.0000	-0.7968***	0.0000	1.0308***	0.0000	1.4947***	0.0000
Leverage*Crisis	0.0043***	0.0000	0.0156***	0.0000	0.0237***	0.0000	0.0889***	0.0000	0.0216***	0.0000	0.0497***	0.0000
VIX*Crisis	0.0002	0.3996	0.0017***	0.0006	-0.0039***	0.0000	-0.0176***	0.0002	-0.0011**	0.0117	-0.0221***	0.0000
10-year yield*Crisis	-0.0946***	0.0000	-0.2532***	0.0000	-0.3503***	0.0000	-0.5723***	0.0000	-0.3101***	0.0000	-0.5011***	0.0000
Gamma*Crisis	0.0053***	0.0000	-0.0226***	0.0000	-0.0503***	0.0000	-0.0406**	0.0270	-0.0388**	0.0000	-0.0813***	0.0000
AdjR^2	0.8509		0.5390		0.4843		0.5312		0.5157		0.5401	

Note: Coefficients and associated partial F-test statistics for the regression $S_t = \beta_0 + \beta_1 r_t + \beta_2 \mathrm{VOL}_t + \beta_3 \mathrm{LEV}_t + \beta_4 \mathrm{L}_t + \delta_0 C + \delta_1 r_t C + \delta_2 \mathrm{VOL}_t C + \delta_3 \mathrm{LEV}_t C + \delta_4 \mathrm{L}_t C + \varepsilon_t$. Where β_0 is an intercept,S_t, LEV_t, r_t, VOL_t, L_t represents the CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. C is a dummy variable for crisis, with C=1 for sample dates during the crisis, and C=0 otherwise. Explanatory variables in the first column are the leverage ratio, VIX, 10-year treasury yield, γ, crisis dummy, its interaction with the leverage ratio, VIX, 10-year Treasury yield and γ. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

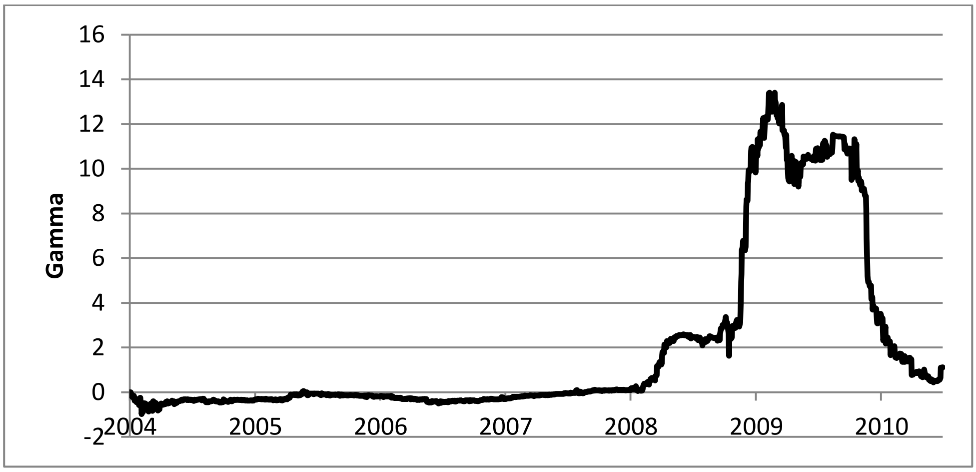
Appendix Table 30. Pooling Regression for CDS Spreads Level with Credit Rating as a Dummy Variable

	Crisis period		Normal period	
	Coefficients	Pr(>F)	Coefficients	Pr(>F)
Constant	0.7728		0.8684	
Leverage	0.1765***	0.0000	0.0655***	0.0000
VIX	0.0541***	0.0000	0.0872***	0.0000
10-year yield	-1.3012***	0.0000	-0.4722***	0.0000
Gamma	0.1280***	0.0000	0.1374***	0.0000
AA	0.1665***	0.0000	-0.4447***	0.0000
A	0.2084		-0.4371	
BBB	0.7882		-0.8205	
Leverage*AA	-0.1644***	0.0000	-0.0585***	0.0000
Leverage*A	-0.1348		-0.0544	
Leverage*BBB	-0.1156		-0.0413	
VIX*AA	-0.0468***	0.0000	-0.0805***	0.0000
VIX*A	-0.0422		-0.0754	
VIX*BBB	-0.0392		-0.0661	
10-year yield*AA	1.0697***	0.0000	0.3731***	0.0000
10-year yield*A	0.9217		0.3586	
10-year yield*BBB	0.7142		0.4001	
Gamma*AA	-0.1137***	0.0000	-0.1247***	0.0000
Gamma*A	-0.1018		-0.1093	
Gamma*BBB	-0.1527		-0.1007	
$AdjR^2$	0.6443		0.7210	

Note: Coefficients and associated partial F-test statistics for the regression $S_t = \beta_0 + \beta_1 r_t + \beta_2 \mathrm{VOL}_t + \beta_3 \mathrm{LEV}_t + \beta_4 \mathrm{L}_t + \delta_{01} R_1 + \delta_{02} R_2 + \delta_{03} R_3 + \delta_{11} r_t R_1 + \delta_{12} r_t R_2 + \delta_{13} r_t R_3 + \delta_{21} \mathrm{VOL}_t R_1 + \delta_{22} \mathrm{VOL}_t R_2 + \delta_{23} \mathrm{VOL}_t R_3 + \delta_{31} \mathrm{LEV}_t R_1 + \delta_{32} \mathrm{LEV}_t R_2 + \delta_{33} \mathrm{LEV}_t R_3 + \delta_{41} \mathrm{L}_t R_1 + \delta_{42} \mathrm{L}_t R_2 + \delta_{43} \mathrm{L}_t R_3 + \varepsilon_t$. Where β_0 is an intercept,S_t, LEV_t, r_t, VOL_t, L_t represents the CDS spread, leverage ratio, risk-free rate, volatility and liquidity, respectively. R_1, R_2 and R_3 indicating credit rating dummy for credit rating classes: R_1=1 for any AA- ~ AAA rated CDS, R_2=1 for any A- ~ A+ rated CDS, R_3=1 for any BBB- ~ BBB+ rated CDS, and zero otherwise. Explanatory variables in the first column are the leverage ratio, VIX, 10-year Treasury yield, γ, credit rating dummy variables, their interaction with the leverage ratio, VIX, 10-year treasury yield and γ. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively. The last row reports the adjusted R^2.

Appendix B.C: Figures

Appendix Figure 6. Time Series Liquidity Measure for BBB- ~ BBB+ Rated CDS



Note: Aggregate γ liquidity measure constructed with all BBB- ~ BBB+ rated CDS spreads.

Part C: Modelling Sovereign Credit Term Structure with Macroeconomic and Latent Variables

Abstract C

I value sovereign CDS (credit default swap) spreads with observable macroeconomic variables and a latent variable under a multifactor affine framework, which allows macro variables to affect the dynamics of the term structure of sovereign credit risk by imposing no-arbitrage assumptions. Studying sovereign CDS spreads of 22 countries, I find that two macro factors (inflation and real output) are able to explain on average 23.06% of the variation of spreads, while the US financial variables explain 46.62% of the latent factor that cannot be captured by macro factors, consistent with the view that sovereign markets are impacted by spillovers from the United States' economy. I further find that incorporating macro factors in a sovereign CDS term structure model improves the out-of-sample performance.

Chapter C1. Introduction

Given the increasing size and volatility of the sovereign debt market, explaining a sovereign country's credit default term structure is important for both credit derivative pricing and investment decisions. Recent rapid widening of sovereign CDS spreads, accompanying the downgrade of many countries' sovereign credit ratings, increases concern about the determinants of CDS spreads and their valuation. This chapter contributes to the literature by proposing a no-arbitrage pricing model for a full term structure of sovereign CDSs, with risk factors including inflation and real output extracted directly from macroeconomic variables, and applying the model to an extensive data set of 22 countries. My model gives several advantages over regression-based empirical approaches. First, it allows analysis of the entire term structure of sovereign credit spreads. Second, pricing macroeconomic variables in the model makes possible a direct comparison of the shocks of macroeconomic variables on sovereign CDSs with different maturities. Third, it is subject to no-arbitrage restrictions and retains tractability by employing a multifactor affine structure. Therefore, the contributions of the chapter are both methodological and empirical.

I study sovereign credit risk by using a monthly data set of sovereign CDS contracts of 22 developed and emerging countries from January 2004 to Sep 2010. A CDS is a contract in which the buyer of protection makes a series of payments (often referred to as CDS spreads) to the protection seller and, in exchange, receives a payoff if a default event[20] occurs. Sovereign CDS contracts with fixed maturity points between 1 and 10 years are actively traded. The availability of the full term structure of sovereign CDS spreads allows me to infer default information for different expiration dates[21].

Literature on sovereign credit risk is categorized under two methodologies: regression and no-arbitrage models. A model of the first type runs a regression of credit default spreads of a certain maturity (usually five years) on several macroeconomic or financial variables and examines the significance and magnitudes of those variables in explaining the spreads (see, for example, Hilscher and Nosbusch, 2010, Longstaff et al., 2011). A model of the second type uses latent factor(s) to value CDS contracts in a risk-neutral world and explains credit default term structure movements based on a no-arbitrage argument (see, for example, Duffie, et al., 2003, Houweling and Vorst, 2005, Pan and Singleton 2008). Regression models yield results that depend on the choices of the explanatory variables as well as on choice of maturity and, furthermore, there is no obvious way of generating coefficient

[20] A default event such as failure to pay, restructuring or rescheduling of debt, credit event repudiation, moratorium and acceleration.

[21] Pan and Singleton (2008) note that, unlike the corporate CDS market where a large majority of trading is on 5-year contracts, the sovereign CDS market has a much more uniform trading volume across maturities. Longstaff et al. (2011) note that the liquidity and bid-ask spreads of sovereign CDS contracts with different maturities are reasonably similar and so the CDS term structure is unlikely to be affected by differential liquidity across maturities.

estimates for maturities other than the given year applied in the regression. In contrast, no-arbitrage models assume the existence of unobservable latent factors that drive the dynamics of default and are, therefore, able to capture all maturities within one system. However, interpretations of the latent factors are then less intuitive. Although there are studies to interpret the meanings of those extracted latent factors, latent-factor models do not price macroeconomic variables directly. For instance, Pan and Singleton (2008) capture most of the variation in the term structure of sovereign CDS spreads with a single latent factor model, and then in a following regression find the associated risk premiums co-vary with several economic and financial measures.

In this study I combine the approaches, adopting a no-arbitrage pricing model for sovereign CDS contracts with both macroeconomic and latent variables. Together with latent variables that contribute to the unexplained spreads variation by macroeconomic variables, I value CDS contracts under a multifactor affine framework. This reduced-form setting allows me to conduct a no-arbitrage analysis on macroeconomic determinants of the term structure of sovereign default spreads. I incorporate the observed macroeconomic variables into the pricing kernel of CDS spreads. There are many macroeconomic variables available with each containing an aspect of the economy; it is, therefore, unrealistic to include all of them in one model. To be parsimonious, I extract two fundamental macro risk factors using a Kalman filter technique to represent the macroeconomy of a country: inflation and real output. For comparison, Ang and Piazzesi (2003) find inflation and economic growth factors strongly impact Treasury bond prices and the dynamics of the yield curve, Wu and Zhang (2008) link inflation and real output factors to the

US Treasury yields and corporate bond spreads, finding evidence that both factors have strong effects on the treasury yield and corporate bond spread term structures. A similar Kalman filter factor extraction technique is applied by Aruoba and Diebold (2010) to monitor US macroeconomic activity in real-time.

My analysis across 22 countries reveals considerable differences. The macroeconomic factors can explain as much as 46.3% of the CDS spreads variation for Japan but as little as 1.8% for Poland. The macro factors have long-lasting effects on the CDS spreads, on average, they explain 21.03%, 22.18%, 23.12%, 24.32% and 24.65% of the variation of 1-, 2-, 3-, 5- and 10-year CDS spreads. Looking for spillover effects from the United States to other regions of the World, I regress the latent factor on three US variables: the CBOE VIX option volatility index, the yield spread between the Moody's 30-year US Baa corporate bond and the 6-month US Treasury bill, and the S&P 500 return. I find these three variables together are able to explain as much as 72.9% of the variation of the latent series for Israel but as little as 12.7% for Greece. The spillover effect is stronger in stress periods than in normal periods. Furthermore, I show that a model with macroeconomic and latent variables outperforms a model with only latent variables. I conduct an out-of-sample analysis in order to relieve the possible over-fitting concern caused by an addition of parameters. On average the model with additional macro factors does a better job by generating a smaller out-of-sample RMSE (root mean square error) than the latent-only model for 14 out of 22 countries, with an averaged cross-country 109 bps RMSE for the former model against 120 bps RMSE for the later. The improvement is more pronounced in normal circumstances before the crisis, suggesting that macro factors become less significant in explaining sovereign credit spreads after the financial crisis.

The chapter is organized as follows. Chapter C2 briefly reviews the literature on determinants of sovereign CDS spread. Chapter C3 presents the pricing models. Chapter C4 reports the data. The empirical results and discussion are presented in Chapter C5, followed by the conclusion in Chapter C6.

Chapter C2. Determinants of Sovereign CDS Spread

Before presenting the pricing model, I review the literature on the determinants of sovereign CDS spreads. Evidence in the literature on the magnitude of determinants is mixed. Several empirical studies focus on domestic inflation or real output as determinants of sovereign credit spreads; for example, Min (1998) shows that a country's macroeconomic fundamentals including domestic inflation rate determine the yield spread in emerging markets; Eichengreen and Mody (2000) find that a few fundamental macroeconomic indicators, including inflation, explain a fraction of spreads on emerging-market debt; Block and Vaaler (2004), together with Mora (2006) and Hill et al. (2010), find that inflation and real output are significant determinants of credit rating level: rating agencies tend to accord higher ratings to countries with lower inflation, resulting in smaller sovereign spreads; Weigel and Gemmill (2006), investigating the creditworthiness of Argentina, Brazil, Mexico and Venezuela, find that country-specific variables explain the variance of yield spreads; Remolona et al. (2008) use a dynamic sovereign CDS panel data model and find that country-specific fundamentals including inflation and real output related variables drive sovereign risk. Aizenman et al. (2013) find macroeconomic factors, especially the inflation factor, are statistically significant and economically important determinants of market-based sovereign risk, after an analysis on sixty countries.

Besides inflation and real output related variables, there are studies finding other determinants contributing to the movement of sovereign credit spreads. Edwards (1984) finds a close relationship between foreign borrowing and a country's default risk; Berg and Sachs (1988) conclude that the trade regime and the degree of income inequality are significant predictors of sovereign default probability; Boehmer and Megginson (1990) find that individual country-specific debt provisions impact debt prices; Duffie et al. (2003) study Russian yield spreads and find evidence that they respond to political events, foreign currency reserves and oil price; Zhang (2008) finds that Argentine sovereign risk is affected by the overall strength of the Argentine economy; Hilscher and Nosbusch (2010) investigate the effects of macroeconomic fundamentals on emerging market sovereign credit spreads and find the volatility of terms of trade has a significant effect.

Several influential papers on global factors other than the above mentioned domestic determinants include Arora and Cerisola (2001), Mauro et al. (2002), Geyer et al. (2004), Gande and Parsley (2005), Weigel and Gemmill (2006), Dailami et al. (2008), Pan and Singleton (2008), Longstaff et al. (2011), Mink and Haan (2013) and Grammatikos and Vermeulen (2012). In particular, Pan and Singleton (2008) apply a single latent factor model on a full term structure of CDS spreads with maturities of 1, 2, 3, 5 and 10 years for Mexico, Turkey and Korea. They find the credit spreads for these three countries are strongly related to the US VIX index. Longstaff et al. (2011) use five-year CDS data for 26 countries and find sovereign credit spreads are driven more by US macroeconomic factors than by a country's local market.

In sum, I conclude from the current literature review that inflation and real output of a country are two key determinants of its sovereign credit spreads, while other factors may also have mixed impacts on its sovereign credit risk. In addition, evidence shows that common global factors mainly from U.S. market have shown stronger spillover effects recently than years ago.

Chapter C3. Pricing Sovereign CDS Contracts

In regard to the roles of inflation, real output and other factors in determining sovereign CDS spreads reviewed in section 2, in this section I propose a no-arbitrage pricing model for sovereign CDS contracts. I first extract two macro factors to represent the aggregate macroeconomy, namely, inflation and real output. Then I develop a no-arbitrage pricing model together with latent factors for the term structure of CDS spreads. Here, latent factors represent those factors that cannot be captured by the two macro factors which have been investigated in literature.

C3.1 Macroeconomic variables

I extract the two macro factors from eight macroeconomic series, including four inflation-related series and four output-related series. The four inflation-related series are the consumer price index (CPI), the producer price index (PPI), the personal consumption expenditure (PCE) deflator and the gross domestic production (GDP) deflator. The CPI is a measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services. The PPI measures average changes in prices received by domestic producers for their output. The PCE deflator is an indicator of the average increase in prices for all domestic personal consumption. The GDP deflator measures the price changes of all officially recognized final goods and services produced within a country.

The four output-related series include the industrial production index (IPI), unemployment rate, the real PCE and the real GDP. The IPI measures real production output, which includes manufacturing, mining, and utilities.

Unemployment rate is an influential statistic and economic indicator meant to represent the prevalence of unemployment in the economy over the previous month, and is directly linked to output. In contrast with PCE and GDP, the real PCE and the real GDP are inflation-adjusted.

The PCE, GDP, real PCE and real GDP are at a quarterly frequency whereas all other series are available at a monthly frequency. I first convert the all four inflation (real output) related series into year-over-year percentage changes, then demean and standardize before extracting the inflation (real output) factor. For series with a quarterly frequency, the Kalman filter estimation method in the next section readily accommodates missing data.

C3.2 Factors extraction

Assuming a sufficient pricing model has n pricing factors: 2 macros and n-2 latent factors (n>2). Let $X \in R^n$ be a vector of Markov process for the n factors, the dynamics process of X under the physical measure P is as follows:

$$dX_t = -kX_t dt + dW_t \tag{1}$$

where W_t is an independent standard Brownian motion vector, k is a n×n matrix with elements reflecting the dependence of X_t on its previous value X_{t-1}. Constrain the k matrix to be

$$\begin{bmatrix} dX_{1,t} \\ dX_{2,t} \\ \cdots \\ dX_{n-1,t} \\ dX_{n,t} \end{bmatrix} = -\begin{bmatrix} k_{11} & 0 & \dots & 0 & 0 \\ k_{21} & k_{22} & 0 & \dots & 0 \\ 0 & 0 & \ddots & 0 & 0 \\ 0 & \dots & 0 & k_{n-1,n-1} & 0 \\ 0 & \dots & 0 & 0 & k_{n,n} \end{bmatrix} \begin{bmatrix} X_{1,t} \\ X_{2,t} \\ \cdots \\ X_{n-1,t} \\ X_{n,t} \end{bmatrix} dt + \begin{bmatrix} dW_{1,t} \\ dW_{2,t} \\ \cdots \\ dW_{n-1,t} \\ dW_{n,t} \end{bmatrix} \tag{2}$$

with $X_{1,t}, X_{2,t}$ being inflation and real output. Allow the inflation and real output factors to be correlated by setting a non-zero element k_{21}, and all latent factors to be independent with the two macro factors by restricting other off-diagonal elements to be zero. Thus, today's value of the inflation factor depends only on its past value, value of the real output factor depends on the past value of the inflation factor and of itself, and value of the latent factors responds to its own past value only. Using Ito's Lemma, the solution of equation (2) has the form:

$$X_t = \text{expm}(-k\Delta t)X_{t-\Delta t} + \int_{t-\Delta t}^{t} \text{expm}(-k(t-s))dW_s \tag{3}$$

where expm is for matrix exponential, $\Delta t = 1/12$ denotes the monthly discrete time interval.

Given the dynamic process in equation (1) and the independence assumption between the two macro factors and the latent factors, I can extract the macro factors X_m from the eight macroeconomic series $Y_{m,t}$, whereas in equation (1) and (2), $dX_{m,t} = -k_{m,t}X_{m,t}dt + dW_{m,t}$, $m = 1,2$ for inflation and real output factors. Impose a linear structure that:

$$Y_t = \text{H}X_{m,t} + \varepsilon_\text{t} \tag{4}$$

H is a 8×2 factor loading matrix to be estimated, $\varepsilon_{m,t}$ is the error term uncorrelated with $X_{m,t}$. To improve identification, constrain the inflation factor to have non-zero loadings only on the four inflation-related series; the real output factor to have non-zero loadings only on the four output related series.

Treating the dynamic process of $X_{m,t}$ and equation (4) as the state and measurement equations, and assuming $\varepsilon_{m,t}$ is normally distributed, I can apply the classic Kalman filter and maximum log likelihood method to estimate parameters for matrix $k_{m,t}$ and H, and to extract the two factor series, where the log-likelihood function is:

$$l_t = -\frac{n}{2}\log(2\pi) - \frac{1}{2}\log(|\mathrm{var}(\widehat{\varpi_t})|) - \frac{1}{2}\varepsilon_{m,t}^{\mathrm{T}}\mathrm{var}(\widehat{\varpi_t})^{-1}\varepsilon_{m,t}$$

where n is the number of observations, $\widehat{\varpi_t}$ is the time-(t-1) forecasts of time-t values of the measurement series, $\mathrm{var}(\widehat{\varpi_t})$ is the covariance matrix of the forecasts. For details, please refer to Aruoba and Diebold (2010).

C3.3 No-arbitrage pricing model

To value CDS spreads under the equivalent martingale measure Q, I allow the dynamics for the n factors as[22]

$$dX_t = k^Q(\theta^Q - X_t)dt + dW_t^Q \tag{5}$$

The different terms $\theta^Q$and k^Q between the equation (1) and (5) incorporate the market price of risk associated with W_t^Q, an independent standard Brownian motion vector under measure Q. For parsimony and consistence with the dependence structure under the physical measure in equation (2), I restrain k^Q to be the following matrix

[22] It is equivalent to assume the market price of risk as $\gamma_0 + \gamma_1 X_t$, with $k^Q\theta^Q = -\gamma_0$ and $k^Q = k + \gamma_1$.

$$\begin{bmatrix} k_{11}^{Q} & 0 & \dots & 0 & 0 \\ k_{21}^{Q} & k_{22}^{Q} & 0 & \dots & 0 \\ 0 & 0 & \ddots & 0 & 0 \\ 0 & \dots & 0 & k_{n-1,n-1}^{Q} & 0 \\ 0 & \dots & 0 & 0 & k_{n,n}^{Q} \end{bmatrix}.$$

The solution of equation (5) becomes:

$$X_t = -\int_{t-\Delta t}^{t} \operatorname{expm}(t-s)\gamma_0 ds + \operatorname{expm}(-k^{Q}\Delta t)\, X_{t-\Delta t}$$

$$+ \int_{t-\Delta t}^{t} \operatorname{expm}(-k^{Q}(t-s)) dW_s{}^{Q} \qquad (6)$$

where $\gamma_0 = -k^{Q}\theta^{Q}$.

Let ϖ represent the CDS spread that is paid continuously, the present value of the premium leg of a CDS can be written under the Q measure as

$$P(\varpi, 0, T) = \mathrm{E}^{\mathrm{Q}}\left[\varpi \int_0^T \exp\left(-\int_0^t (r_s + \lambda_s) ds\right) dt\right] \qquad (7)$$

where r is the risk-free rate and λ is the credit spread. Similarly, if a credit event occurs then the protection seller pays the buyer par value and, in return, receives a bond issued by the same reference entity[23]. The present value of the protection leg of a CDS under the Q measure is

$$PR(w, 0, T) = \mathrm{E}^{\mathrm{Q}}\left[w \int_0^T \lambda_t \exp\left(-\int_0^t (r_s + \lambda_s)\, ds\right) dt\right] \qquad (8)$$

with w being the loss rate of the par value in the event of default[24]. Equating the values of both legs returns the CDS spread

[23] Or, in the cash settlement case, the protection seller pays the buyer the cash difference between par value and the market price of the bond.

[24] As in Pan and Singleton (2008), Longstaff et al (2011), I assume that the loss rate w is 0.75 throughout the whole study.

$$\varpi = \frac{\mathrm{E}^{\mathrm{Q}}\left[w\int_0^T \lambda_t \exp\left(-\int_0^t (r_s+\lambda_s)ds\right)dt\right]}{\mathrm{E}^{\mathrm{Q}}\left[\int_0^T \exp\left(-\int_0^t (r_s+\lambda_s)ds\right)dt\right]} \tag{9}$$

Without loss of generality, assume that the risk-free rate is independent from default spread, such that I do not need to specify the risk-neutral dynamics of the risk-free rate in order to solve equation (9). The independence assumption is made in many papers; for example by Longstaff et al. (2005), Pan and Singleton (2008). Let the value of a risk-free zero-coupon bond with maturity T be given by

$$D(T) = \mathrm{E}^{\mathrm{Q}}\left[\exp\left(-\int_0^T r_t\, dt\right)\right] \tag{10}$$

Equation (10) can be recast as

$$\varpi = \frac{\mathrm{E}^{\mathrm{Q}}\left[w\int_0^T \lambda_t \exp\left(-\int_0^t \lambda_s ds\right)D(t)dt\right]}{\mathrm{E}^{\mathrm{Q}}\left[\int_0^T \exp\left(-\int_0^t \lambda_s ds\right)D(t)dt\right]} \tag{11}$$

Let the instantaneous credit spread for each country be an affine function of the pricing factors

$$\lambda(X_t) = a + b^{\mathrm{T}}X_t \tag{12}$$

Given the dynamic process in equation (5) and the affine structure in equation (12), standard results in Duffie et al. (2000) make it straightforward to derive closed-form solutions. Appendix C.B shows the value of the denominator is

$$\int_0^{\mathrm{T}} \exp\left(a_{\mathrm{CDS}} + {b_{\mathrm{CDS}}}^{\mathrm{T}}X_t\right) D(t)dt \tag{13}$$

with a_{CDS}, b_{CDS} being solutions to the following ODEs:

$$a_{CDS}' = a + {b_{CDS}}^{\mathrm{T}}\gamma_0 - \frac{1}{2}{b_{CDS}}^{\mathrm{T}}b_{CDS} \tag{14}$$

$$b_{CDS}' = b + (k^Q)^{\mathrm{T}}b_{CDS}$$

subject to the boundary conditions $a_{CDS} = b_{CDS} = 0$ at T, and ${b_{CDS}}^{\mathrm{T}}$ denotes the transpose of matrix b_{CDS}.

The value of the nominator is

$$w\int_0^{\mathrm{T}} \exp(a_{CB} + {b_{CB}}^{\mathrm{T}} X_t) \times (a + A_{CB} + {B_{CB}}^{\mathrm{T}} X_t) D(t) dt \tag{15}$$

with a_{CB}, b_{CB} being solutions to the following ODEs:

$$a_{CB}{}' = a + {b_{CB}}^{\mathrm{T}}\gamma_0 - \frac{1}{2} {b_{CB}}^{\mathrm{T}} b_{CB} \tag{16}$$

$$b_{CB}{}' = b + (k^Q)^{\mathrm{T}} b_{CB}$$

subject to the boundary conditions $a_{CB} = b_{CB} = 0$ at T . A_{CB}, B_{CB} satisfy the ODEs

$$A_{CB}{}' = {B_{CB}}^{\mathrm{T}}\gamma_0 - {b_{CB}}^{\mathrm{T}} B_{CB} \tag{17}$$

$$B_{CB}{}' = (k^Q)^{\mathrm{T}} B_{CB}$$

subject to the boundary conditions $A_{CB} = 0$ and $B_{CB} = b$at T, b_{CB} is the same as in equation (16).

Chapter C4. Data Description

I obtain mid-market sovereign CDS spreads with maturities 1, 2, 3, 5 and 10 years from Datastream. In order to be included in the sample, a sovereign CDS must have available trading data starting no later than August 2004. In addition, its country must have sufficient inflation and real output-related macro data from either Datastream or the Federal Reserve Bank of St. Louis to extract the two macro factors. This screening allows 22 countries into my sample[25], covering the period from January 2004 to September 2010. All sovereign CDS spreads are US dollar denominated. I proxy 1-, 2- 3-, 5- and 10-year risk-free rates with same maturity Treasury yields collected from the Federal Reserve Bank.

Table 31 presents summary statistics for monthly spreads in bps (basis points) for five-year sovereign CDSs. Both mean and standard deviation (SD) values differ considerably across countries; for example, Japan has the smallest mean spread at 24.59 bps and SD at 27.93 bps, contrasted with the largest mean spread at 707.30 bps and SD at 659.24 bps for Venezuela. Although Greece's mean spread is the 11th largest in my sample, its SD at 215.67 bps and maximum spread at 926.14 bps are both the 2nd largest, next only to Venezuela. The number of observations is similar for all countries.

[25] The filtering process excludes those countries including Portugal, Spain and the United States into our sample. Giving the importance of their sovereign credit risk in financial market, the list of countries in this thesis restricts a comprehensive study and adding those countries into analysis will be a further research topic.

The smallest Japanese CDS spreads and the largest Venezuelan spreads are noteworthy. Japanese sovereign CDS spread is smallest despite of its high public debt. Shino and Takahashi (2010) investigate the relationship between CDS spreads and fiscal risk variables. They find that although CDS spreads reflect the changes of public debt amounts, the degree of interrelation varies by countries. By comparing 26 countries for which both sovereign CDS outstanding data and government debt data are available, Shino and Takahashi (2010) show that Japan, the United States and the United Kingdom hold only around 5% of sovereign CDSs, although they have almost two-thirds of the total public debt. Therefore investors holding these three countries' government bonds seem not to hedge against the default risk by purchasing their sovereign CDSs. Regressing sovereign CDS spreads on fiscal risk related variables, Shino and Takahashi (2010) find the R^2 is generally high and the coefficients are statistically significant for those continental European countries, while the R^2 is extremely low and the coefficients are not significant for Japan, the United States and the United Kingdom. Therefore in investors' opinion, the default risk is low for Japan although it has high public debt, it is less necessary to hedge against the default risk of Japan, which results in a small sovereign CDS spreads. The impact of trading behaviour on sovereign CDS spreads is a future research topic.

A report published by CMA (2010), the world's leading source of independent OTC market data, shows that Venezuela is the world's riskiest sovereign, with a 48.5% cumulative probability of default within the next five years. Longstaff et al. (2011) find exchange rate is a determinant of sovereign credit risk; Pan and Singleton (2008) argue that the behaviour of the South

American CDS spreads was largely dominated by the political turmoil. The impact of exchange rate and political factors on sovereign CDS spreads of those South American countries is an interesting topic for future research.

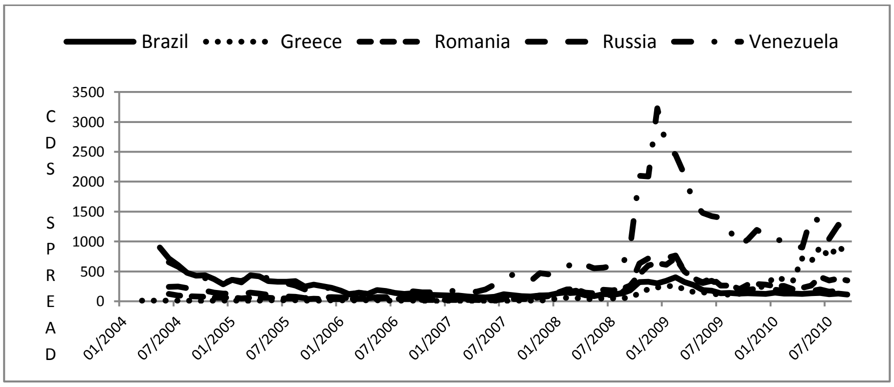
Figure 7 illustrates the movement of CDS spreads for the five countries with the largest standard deviations. Appendix Figure 12 plots the CDS spreads of all countries in my sample. CDS spreads are relatively low and stable before the beginning of 2007, become volatile after the end of 2007 and reach their maximum around 2009, except those for Greece, which continue to increase till the end of the sample period.

Table 31. Descriptive Statistics for Sovereign CDS Spreads (bp)

Country	Mean	SD	Min	Median	Max	*N*
Austria	31.3667	48.5494	1.5000	3.0000	235.0000	81
Brazil	215.4651	153.7080	62.6000	137.7450	900.2000	77
Chile	58.7144	58.2634	7.8000	32.5000	254.2200	81
Colombia	208.1625	104.9738	77.0000	164.0200	490.0000	76
Croatia	121.8660	120.2530	15.2000	65.0000	516.0000	81
Greece	119.6072	215.6703	5.0000	14.5000	926.1400	79
Hungary	124.9575	142.8755	10.2000	36.9500	563.2800	80
Israel	72.3153	57.6273	16.5000	40.0000	275.0000	75
Italy	48.7690	59.7642	5.6000	12.2000	229.5900	81
Japan	24.5949	27.9272	3.0000	7.5000	96.9100	81
Korea	84.1569	91.1881	14.7000	48.7000	437.5000	81
Malaysia	70.6619	64.5694	13.0000	37.2000	296.6700	77
Mexico	118.6622	83.0364	29.0000	102.7000	458.2300	81
Peru	186.0531	105.6336	62.5000	144.8375	576.6000	78
Philippines	270.7456	129.4990	99.2000	222.3000	515.0000	81
Poland	67.0856	76.9443	8.0000	26.0000	362.5000	81
Romania	165.2057	168.5659	17.5000	78.8500	720.5300	76
Russia	171.9436	169.3233	38.5000	124.1000	764.5800	76
Slovak	39.5456	45.7632	4.2000	15.8000	215.0000	81
South Africa	124.0585	97.9769	24.2000	96.2000	465.0000	81
Thailand	80.6556	64.4620	27.0000	44.2000	300.0000	81
Venezuela	707.3048	659.2428	123.0000	448.2500	3229.3000	76

Note: Summary statistics for monthly spreads in basis points (bp) for five-year sovereign CDS from January 2004 to September 2010. The column head is for country name, mean, standard deviation, minimum, median, maximum and the number of observations, respectively.

Figure 7. Time Series Plot of Five Sovereign CDS Spreads (bps)



Note: Plot of sovereign CDS spreads for five countries with the largest standard deviation spreads.

Chapter C5. Empirical Results and Discussion

In this section I report the two extracted macro factors discussed in section C3.2 and discuss the relevance of these factors for sovereign CDS spreads. I then investigate the issue of the number of latent factors sufficient for CDS spreads valuation via a principal component analysis (PCA). I investigate the effectiveness of macro factors in explaining sovereign credit spreads of each country, selecting Greece as a case study to illustrate my pricing model.

C5.1 Extracted macro factors

Table 32 reports the parameter estimates under a physical measure and the values of the t-statistics on time series dynamics of the two macro factors $dX_{m,t} = -k_{m,t}X_{m,t}dt + dW_{m,t}$, where $k_{m,t}$, $m = 1,2$, controls the dynamics of the macro factors. k_{11} determines the mean-reverting speed of inflation and the impact magnitude of the lagged value of the inflation factor on its conditional mean. k_{21} reflects the relationship between the past value of inflation and the change of real output and, together with k_{22}, it decides the dynamics of the real output factor. A negative k_{21} value indicates a positive respond of real output to inflation.

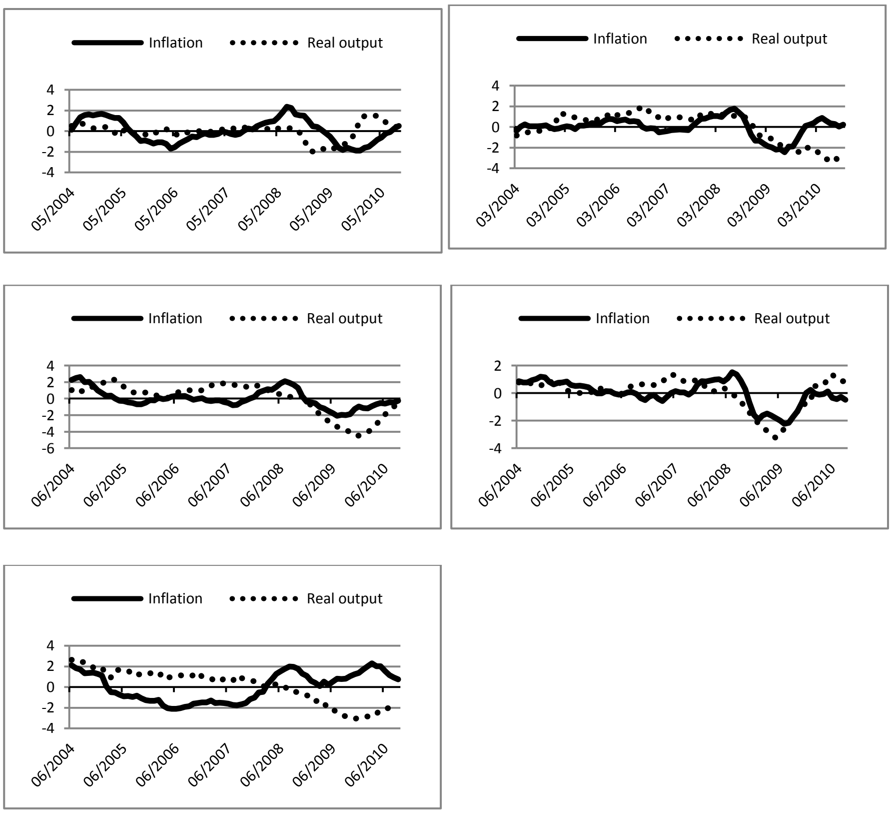
Given the parameter estimates, I can extract updated values of the two macro factors from the eight observed macroeconomic series. Figure 8 plots the extracted inflation and real output factors for five countries with the largest standard deviations of spreads. Appendix Figure 13 shows the macro factors for all countries. Generally, inflation is high at the beginning of 2004, it remains low from the beginning of 2005 to the middle of 2007, increases at the beginning of 2008, and drops dramatically at the end of 2008, doubtless related to the financial crisis, but recovers gradually in 2010. Real output is relatively high and stable before 2008, plummets at the middle of 2008 and recovers mostly in 2010, with the exception of Greece. Greek output continues to decrease until the end of the sample period, reflecting the worsening economy and the rising CDS spreads in Figure 7.

Table 32. Time-series Dynamics Estimation of the Two Macro Factors

	Estimate			t-statistics		
	k11	*k21*	*k22*	*k11*	*k21*	*k22*
Austria	0.7324*	1.2865**	0.1234	1.6740	2.3049	0.7270
Brazil	0.5006	1.1312***	0.7383	1.5509	2.8191	1.4919
Chile	0.6899*	-1.2456**	0.9714*	1.7056	-2.1209	1.9831
Colombia	0.2210	0.1724	1.2355	1.0002	0.5203	1.5651
Croatia	0.5430	-2.7163***	0.5091**	1.1667	-3.8572	2.6180
Greece	0.7421*	-0.8719*	0.1742	1.7744	-1.8310	0.8900
Hungary	0.6695	0.0204	0.5932	1.6224	0.0435	1.4908
Israel	0.8509*	-1.2042	0.8484*	1.7902	-1.6577	1.9668
Italy	0.4432	0.6466	0.2054	1.4539	1.5698	0.7608
Japan	0.4572	1.2732***	0.1900	1.5423	3.4195	0.8390
Korea	0.6295*	1.5029***	1.0796**	1.7060	3.1554	2.0106
Malaysia	0.6812*	0.4222	0.5957	1.7212	0.6488	0.8369
Mexico	0.7460	1.3052**	0.5483	1.6133	2.4148	1.5431
Peru	0.4651	1.0981**	0.2556	1.5336	2.3744	0.7659
Philippines	0.5260	0.2382	1.4999*	1.5630	0.5728	1.8138
Poland	0.8700*	-0.3183	0.0933	1.8290	-0.6327	0.8942
Romania	0.3066	-0.8543*	0.4348*	1.0574	-1.8513	1.7970
Russia	0.6687	0.5401	0.2429	1.6006	0.9859	0.8211
Slovak	0.3572	-1.6968***	1.1063***	1.3601	-2.8119	2.7375
South Africa	0.4231	1.1426**	0.1910	1.3906	2.4811	0.8279
Thailand	0.8938*	0.4739	0.9625	1.8705	0.7729	1.4195
Venezuela	0.2294	0.1691	0.1592	1.0491	0.5294	0.8271

Note: Parameter estimates and the values of the t-statistics on time series dynamics of the two macro factors, $dX_{m,t} = -kX_{m,t}dt + dW_{m,t}$, where k matrix is defined as in equation (2) under physical measure. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Figure 8. Time Series Plot of Extracted Macro Factors



Note: Plots of the extracted inflation and real output factors for five countries with the largest standard deviation spreads. Plots from the top left to the bottom right are for country Brazil, Greece, Romania, Russia and Venezuela, respectively. Y axis is the standardized value.

C5.2 Number of latent factors

I have not so far determined the number of latent factors for CDS spread valuation, except the n-2 latent factors definition in section C3.2. To determine the number, I run an ordinary least square (OLS) regression of CDS spreads of each maturity on the inflation and real output factor, then conduct a standard principal component analysis (PCA) on the regression residuals for each country. PCA uses an orthogonal transformation to convert a set of observations (regression residuals of each maturity) of possibly correlated variables into a set of values of linearly uncorrelated variables, the principal components. It can be used to identify the number of common factors by analyzing the percentage of each component's ability to explain the variance of the whole set of observations[26].

Table 33 presents the results of an OLS regression of CDS spreads on the inflation and real output factors, $\text{CDS}_t = \alpha + \beta_1 \text{Inflation}_t + \beta_2 \text{Output}_t + \varepsilon_t$. P-value is the averaged p-value for the F-statistics with null hypothesis that $\beta_1 = \beta_2 = 0$. AdjR^2 is the averaged adjusted R^2 across maturity 1, 2, 3, 5, and 10 years. PC1 is the percentage that the first principal component can explain of the variance of ε_t. The p-values all smaller than 0.01 suggests that my extracted inflation and real output factors are strongly significant in explaining sovereign CDS spreads. On average, the simple OLS regression is able to explain 36.67% of the variation of CDS spreads across all countries and all maturities. Both results indicate the high relevance of the macro factors to CDS spreads.

The first PC alone is able to explain on average 96.65% of the variance of the regression residuals that cannot be explained by the two macro factors, suggesting that one latent factor is sufficient. Therefore equation (2) becomes

$$\begin{bmatrix} dX_{1,t} \\ dX_{2,t} \\ dX_{3,t} \end{bmatrix} = -\begin{bmatrix} k_{11} & 0 & 0 \\ k_{21} & k_{22} & 0 \\ 0 & 0 & k_{33} \end{bmatrix} \begin{bmatrix} X_{1,t} \\ X_{2,t} \\ X_{3,t} \end{bmatrix} dt + \begin{bmatrix} dW_{1,t} \\ dW_{2,t} \\ dW_{3,t} \end{bmatrix} \qquad (18).$$

[26] Recall that the PCA analysis on regression residuals is only a method of approximating the number of latent factors; the real question is how to find the number of factors in a no-arbitrage framework.

Table 33. Regression results of CDS spreads on two macro factors

Country	P-value	AdjR^2	PC 1	*N*
Austria	0.0000	0.5334	0.9837	81
Brazil	0.0028	0.1276	0.9333	77
Chile	0.0002	0.1769	0.9708	81
Colombia	0.0007	0.1793	0.9034	76
Croatia	0.0000	0.6761	0.9707	81
Greece	0.0000	0.6910	0.9775	79
Hungary	0.0000	0.5202	0.9758	80
Israel	0.0000	0.3821	0.9770	75
Italy	0.0089	0.0955	0.9898	81
Japan	0.0000	0.3469	0.9670	81
Korea	0.0000	0.4127	0.9945	81
Malaysia	0.0000	0.4068	0.9808	77
Mexico	0.0000	0.5243	0.9664	81
Peru	0.0000	0.3141	0.8904	78
Philippines	0.0011	0.1616	0.9223	81
Poland	0.0000	0.2693	0.9876	81
Romania	0.0000	0.3179	0.9918	76
Russia	0.0000	0.4195	0.9755	76
Slovak	0.0020	0.1613	0.9862	81
South Africa	0.0000	0.5915	0.9358	81
Thailand	0.0000	0.2981	0.9886	81
Venezuela	0.0000	0.4605	0.9949	76

Note: Results of an OLS regression of CDS spreads on the inflation and real output factors, $\text{CDS}_t = \alpha + \beta_1 \text{Inflation}_t + \beta_2 \text{Output}_t + \varepsilon_t$. P-value is the averaged p-value for the F-statistics with null hypothesis that $\beta_1 = \beta_2 = 0$, AdjR^2 is the averaged adjusted R^2 across maturity 1, 2, 3, 5, and 10 years. PC 1 is the percentage that the first principal component can explain the variance of ε_t. *N* is the number of observations.

C5.3 The Greek case study

Before applying the model to the whole set of countries in the sample, it is useful to illustrate via a case study of Greek sovereign CDSs, sampling from March 2004 to September 2010. Greece has suffered since the breakout of the crisis and, as noted earlier, both the maximum value and standard deviation of Greek sovereign CDS spreads are the second largest among all countries. Worse, unlike those of other countries reaching their peaks at the beginning of 2009, Greek CDS spreads continue to increase to the end of my sample period.

Table 34 reports the factor loadings matrix H and associated t-statistics for equation (4) $Y_{m,t} = \mathrm{H}X_{m,t} + \varepsilon_{m,t}$. All eight macroeconomic variables are significant in extracting the inflation and real output factors, suggesting their indispensable roles in reflecting the Greek economy. The coefficient signs for all four inflation-related series are positive; the only negative sign is for unemployment because of the inverse relationship between the unemployment and real output.

Table 35 presents estimates for the market prices of risk for equation (5) $dX_t = k^Q(\theta^Q - X_t)dt + dW_t^Q$ via the extended Kalman filter technique and maximum likelihood estimation method outlined in Appendix C.A. Table 36 shows results for the instantaneous credit spread function for equation (12) $\lambda(X_t) = a + b^{\mathrm{T}}X_t$. The intercept, α, measures the long-run mean instantaneous spread for Greece, which is estimated at 1.20%. The loading coefficient, *b*, measures the contemporaneous response of the instantaneous spread to unit shocks on the three factors. All loading estimates are strongly significant, suggesting again the necessity to price them all in. The coefficient for inflation is positive and is negative for real output, as expected, indicating higher inflation or lower real output increases the short-term Greek sovereign CDS spread, and vice versa.

Based on the above estimation, I value the Greek sovereign CDS spreads of all maturities in one system as in equation (11). Figure 9 plots the model pricing errors for CDS's with 1-, 5- and 10-year maturities, measured by the market observed spreads minus the model-implied spreads. The errors are relatively small before the end of 2009 and increase dramatically after that due to the rising volatility of CDS spreads. The averaged RMSE is shown in Table 37 as 80.12 bps.

In order to examine the variance explained by macro factors, I calculate the model-implied CDS spreads (Macro spreads) without a latent factor by restricting the elements in the *k* matrix and the loading coefficient in equation (12) for the latent factor to zero. Given the independence structure between the macro and latent factors, the variance explained by macro factors can be estimated approximately as var(Macro)/var(Full), where Macro is the model-implied Macro spreads and Full is the model-implied spreads including both the macro and latent factors, and var(x) is the variance of x. Table 38 reports the results for Greece: macro factors can explain as much as 39.68%, 39.58%, 39.39%, 38.66% and 35.34% of the variation of CDS spreads with 1-, 2-, 3-, 5- and 10-year maturity, respectively.

Table 34. Macro Factor Loadings for Macroeconomic Variables for Greece

	Inflation	Real output
Loading		
CPI	0.9461***	0.0000
PPI	1.1179***	0.0000
PCE	0.7242***	0.0000
GDP	0.4370**	0.0000
IP	0.0000	0.4344***
Unemploy	0.0000	-0.6684***
Real.PCE	0.0000	0.5879***
Real.GDP	0.0000	0.5330***
t-statistics		
CPI	9.2375	-
PPI	12.2142	-
PCE	4.0855	-
GDP	2.1319	-
IP	-	5.6267
Unemploy	-	-3.2248
Real.PCE	-	3.4924
Real.GDP	-	5.5182

Note: Factor loadings matrix H and associated t-statistics for macro factors extraction, $Y_t = \mathrm{H}X_{m,t} + \varepsilon_t$, where the macroeconomic variables in the first column are CPI, PPI, PCE, GDP, IP, Unemployment, Real PCE and Real GDP. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Table 35. Market Prices of Risk for Greece

	k			Theta (Θ)
Estimates				
Inflation	0.0304***	0.0000	0.0000	-77.9451***
Real output	-0.1004***	0.1120***	0.0000	-83.6446***
Latent	0.0000	0.0000	0.1151***	1.1992
t-statistics				
Inflation	5.3290	-	-	-63.8879
Real output	-7.7592	13.5788	-	-146.0296
Latent	-	-	11.5362	1.1458

Note: K and Θ matrix estimates for Greece, $dX_t = k^Q(\theta^Q - X_t)dt + dW_t^Q$. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Table 36. Instantaneous Credit Spread for Greece

	Estimates	t-statistic
Intercept (α)	0.0120***	7.0774
Inflation	0.0114***	5.4957
Real output	-0.0163***	-13.0276
Latent	0.0399***	9.5387

Note: The intercept and factor loadings for the instantaneous credit spread function for Greece, $\lambda(X_t) = a + b^{\mathrm{T}} X_t$. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Table 37. RMSE (bps) for All Sovereign CDSs

RMSE	Full	Macro	*N*
Austria	16.2094	31.8107	81
Brazil	67.7352	131.2934	77
Chile	22.3083	51.3730	81
Colombia	52.7619	95.9567	76
Croatia	40.0969	77.5258	81
Greece	80.1207	143.1907	79
Hungary	46.0783	104.2985	80
Israel	20.0843	43.4350	75
Italy	19.7450	52.2359	81
Japan	13.8120	20.4967	81
Korea	37.5229	75.1299	81
Malaysia	22.6547	46.3978	77
Mexico	33.7528	64.1293	81
Peru	50.5007	93.1204	78
Philippines	54.0045	117.8085	81
Poland	25.0907	68.1885	81
Romania	59.6792	148.2858	76
Russia	72.0526	155.0629	76
Slovak	16.4553	38.5889	81
South Africa	37.7203	83.3780	81
Thailand	22.3233	51.3963	81
Venezuela	268.4027	600.8925	76

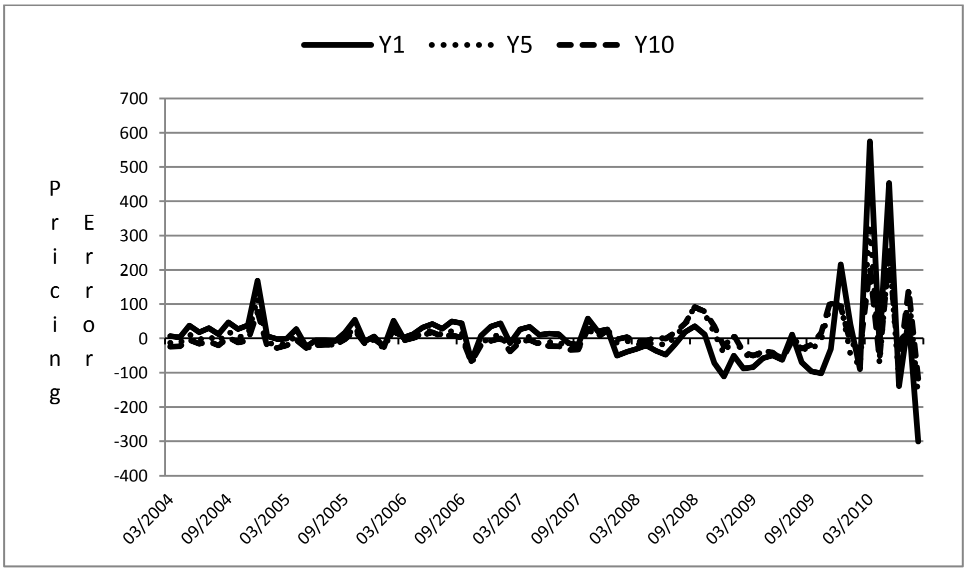
Note: Averaged RMSE (root mean squared error) in bps for the sovereign CDS spreads pricing error across all maturities, where pricing errors are measured by the market observed spreads minus the model-implied spreads. Full is for the model with all three pricing factors, and Macro is for the model without the latent factors. *N* is the number of observations.

Table 38. Variance Explained by Macro Factors

	Year 1	Year 2	Year 3	Year 5	Year 10	Average	*N*
Austria	0.2464	0.2474	0.2482	0.2496	0.2520	0.2487	81
Brazil	0.0962	0.1252	0.1546	0.2094	0.2941	0.1759	77
Chile	0.0804	0.0786	0.0769	0.0737	0.0670	0.0753	81
Colombia	0.2330	0.3221	0.3870	0.4540	0.4456	0.3683	76
Croatia	0.3657	0.3678	0.3695	0.3719	0.3672	0.3684	81
Greece	0.3968	0.3958	0.3939	0.3866	0.3534	0.3853	79
Hungary	0.2861	0.2821	0.2781	0.2702	0.2484	0.2730	80
Israel	0.1778	0.1732	0.1690	0.1617	0.1480	0.1659	75
Italy	0.0596	0.0579	0.0563	0.0534	0.0470	0.0548	81
Japan	0.3315	0.4003	0.4550	0.5274	0.5997	0.4628	81
Korea	0.2460	0.2475	0.2480	0.2453	0.2186	0.2411	81
Malaysia	0.2674	0.2709	0.2720	0.2690	0.2451	0.2649	77
Mexico	0.2846	0.2989	0.3125	0.3344	0.3548	0.3170	81
Peru	0.1456	0.1578	0.1722	0.2044	0.2745	0.1909	78
Philippines	0.0949	0.1336	0.1752	0.2538	0.3734	0.2061	81
Poland	0.0415	0.0228	0.0146	0.0082	0.0041	0.0182	81
Romania	0.1834	0.1790	0.1725	0.1569	0.1174	0.1619	76
Russia	0.2079	0.2040	0.1994	0.1882	0.1565	0.1912	76
Slovak	0.0992	0.1288	0.1506	0.1765	0.1917	0.1494	81
South Africa	0.3356	0.3416	0.3473	0.3573	0.3717	0.3507	81
Thailand	0.1828	0.1734	0.1652	0.1522	0.1340	0.1615	81
Venezuela	0.2650	0.2714	0.2696	0.2456	0.1585	0.2420	76

Note: Variance explained by the two macro factors: inflation and real output, defined as var(Macro)/var(Full), where Macro and Full are explained in context. *N* is the number of observations.

Figure 9. Time Series Plot of Model Pricing Errors (bps) for Greece



Note: Plot of model pricing errors of Greek sovereign CDS spreads with 1-, 5- and 10-year maturities. Pricing errors are defined as the difference between model implied spreads and market observed spreads.

C5.4 Countries analysis

Having illustrated the model with Greece, I now extend the analysis to all countries in my sample.

C5.4.1 Model estimation

Appendix Table 41 reports the factor loadings matrix H and associated t-statistics for macro factors extraction $Y_{m,t} = \mathrm{H}X_{m,t} + \varepsilon_{m,t}$. Similar to the case for Greece, nearly all macroeconomic variables are significant for the extraction of both inflation and real output factors. Appendix Table 42 shows the values of the k matrix and Θ under the risk-neutral measure. Comparing the k matrix under the physical measure shown in Table 32 in chapter C5.1, the difference of k matrix, together with the strongly significant Θ in Appendix Table 42, suggests substantial market risk premiums related to uncertainty about future credit events.

Instantaneous credit spread gauges the default risk of a very short future moment of each sovereign country. Appendix Table 43 lists the intercept and factor loadings for the instantaneous credit spread function, $\lambda(X_t) = a + b^{\mathrm{T}}X_t$. Since it measures the long-run mean instantaneous spread, the intercept, α, directly reflects the expected short-term default spread of each country. The bottom plot of Figure 10 further illustrates the instantaneous CDS spread, which varies dramatically across countries; Japan has the smallest instantaneous spread at 9.42 bps while Venezuela has the largest at 618.10 bps, almost 66 times higher. The loading coefficient, b, measures the contemporaneous response of the instantaneous spread to unit shocks on the three factors. Generally the response is positive for the inflation factor and is negative for the real output factor, consistent with the literature that a higher inflation rate (lower real output) leads to a larger sovereign credit spread; see, for example, Block and Vaaler (2004), Mora (2006) and Hill, et al. (2010).

C5.4.2 Model fit

Table 37 presents the results for the RMSE, a measure of model performance. Not surprisingly, my model generates the largest RMSE for Venezuela, at 268.40 bps, and the smallest for Japan, at only 13.81 bps. Due to space limitation, I plot only the 5-year CDS pricing errors in Appendix Figure 14; the errors are generally small before the financial crisis and increase afterwards. Comparing with the spreads statistics in Table 31, the pricing errors are relatively small from a percentage perspective. Using the restricted model with only the macro factors increases the RMSE dramatically; for example, it is 59.68 for Romanian CDS spreads for the full model and jumps to

148.29 bps for the model without a latent factor, suggesting the insufficiency of a model with only macro factors for CDS spread valuation.

An important feature of a good pricing model is its ability to explain the level of sovereign CDS spreads. We run a regression as an empirical investigation

$$CDS_{i,t}^{obs} = \beta_{0,i} + \beta_{1,i} CDS_{i,t}^{m} + \varepsilon_{i,t}$$

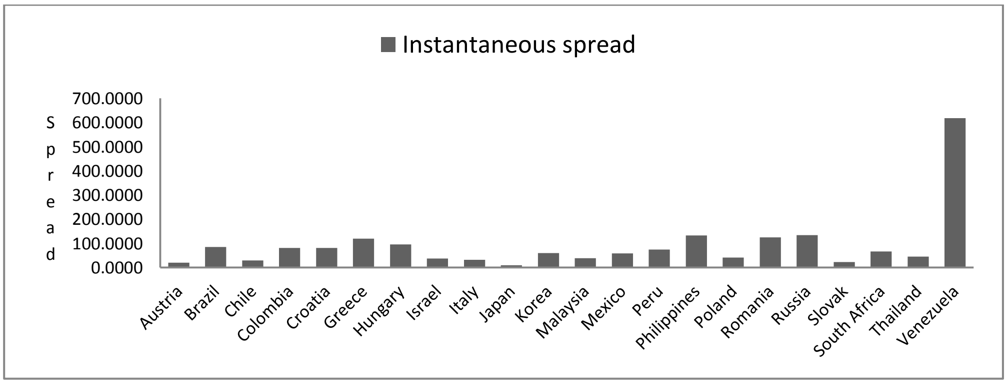
Where $CDS_{i,t}^{obs}$ is the observed CDS spread for country i at time t, and $CDS_{i,t}^{m}$ is the CDS spread estimated by model. If a model is correctly specified and adequately reflects the level of CDS spreads of country i, the above regression will generate a zero constant $\beta_{0,i}$ and a unit coefficient $\beta_{1,i}$. Appendix Table 44 provides the coefficient estimates of the regression for each country. First, the constant term β_0 remains insignificant for all countries; second, the slope estimate β_1 is strongly significant at 1% level, the null hypothesis that $\beta_1 = 1$ is only rejected at 5% level for Croatia and Russia; third, the regression yields an average adjusted R^2 of 83.41%, with the highest value of 90.41% for Greece and the lowest value of 64.48% for Colombia. In summary, Appendix Table 44 suggests that our model successfully replicates the sovereign CDS spread level.

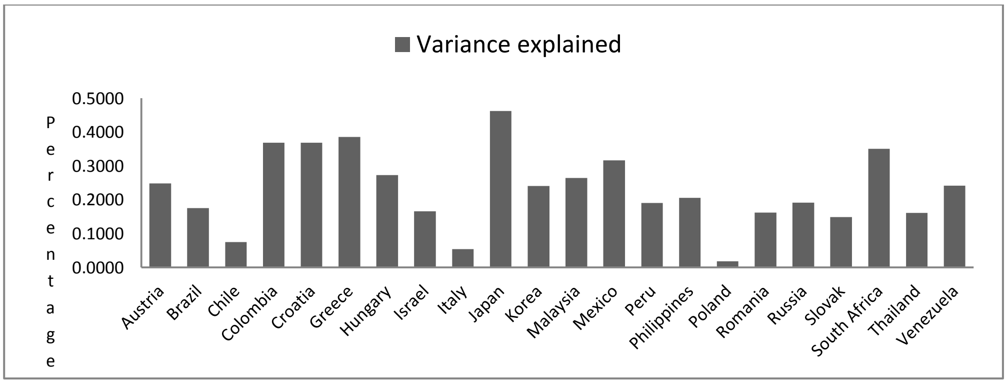
C5.4.3 Macro factors variance explanation

Table 38 reports the variance explained by the two macro factors. The percentage that macro factors can explain varies greatly across countries - on average, they explain 23.06% of the variation of the term structure of sovereign CDS spreads, with the largest percentage for Japan at 46.28%, while they can barely explain the variation of Polish credit spreads. Across the term structure, the macro factors can, on average, explain 21.03%, 22.18%, 23.12%, 24.32% and 24.65% of the variation of 1-, 2-, 3-, 5- and 10-year CDS spreads. The increasing explanatory power suggests that the impacts of the macro factors are long-lasting and are even larger for sovereign CDS with a longer maturity. The average explanatory power, 23.06%, is much lower than the 85% found by Ang and Piazzesi (2003) for US Treasury yields; indeed, 85% is much larger than the largest percentage 46.28% for Japan, but this is not surprising because macro factors have more direct influence on Treasury yields than on CDS spreads since CDS spreads incorporate other impacting factors that cannot be captured by macro variables (Duffie et al. 2003)[27].

[27] I cannot compare directly with the explanatory power of the two macro factors on US sovereign CDS spreads because US is not a country in my sample. The earliest US sovereign CDS spread I can obtain is December 2007, the short sample periods restrict my analysis.

Figure 10. Instantaneous CDS Spread (bps) and Variance Explained by Macro Factors





Note: The top plot shows the long-run mean instantaneous spread (bps) and the bottom plot shows the variance explained by the two macro factors for each country.

C5.5 Spillover effect from the US

Researchers have found a strong spillover effect from the United States to other regions of the World, reflecting to the leading role of the United States market. For example, Pan and Singleton (2008) provide evidence that credit risk in Mexican, Korean and Turkish sovereign markets is influenced by real economic growth in the United States, by conducting a regression analysis of the correlations between sovereign credit risk premiums and three US financial and economic variables. Longstaff et al. (2011) find that sovereign credit spreads are even more related to the US market than they are to local markets. Gande and Parsley (2005) examine cross-border debt market linkages by concentrating on the transmission of news events, and present asymmetric spillover evidence. I investigate this effect by examining the percentage of the extracted latent series that the US market variables are able to explain, since, by definition, the latent factor is independent of the two domestic macro factors and reflects the possible global determinants and local determinants other than the two macro factors. I regress the latent series $X_{L,t}$ on several variables representing the US financial market, specifically, the CBOE VIX option volatility index, the yield spread between the Moody's 30-year US Baa corporate bond and the 6-month US Treasury bill, and the S&P 500 return. $X_{L,t} = \beta_0 + \beta_1 \mathrm{VIX}_t + \beta_2 \mathrm{YieldSpread}_t + \beta_3 \mathrm{SP500}_t + \varepsilon_t$. The first two variables are similar to those in Pan and Singleton (2008). The VIX is a measure of the implied volatility of S&P 500 index options and is sometimes referred to as the fear index of the US financial market. The yield spread is a measure of expected default premium reflecting the US macroeconomic and financial market development. The S&P 500 return is often viewed as a measure of the overall business climate of the US economy; for instance, Collin-Dufresne et al. (2001) investigate it as a determinant of credit spread changes.

Table 39 reports the regression results. The VIX is the most significant among the three explanatory variables; it is significant at the 10% level for 21 out of 22 countries[28], suggesting a strong spillover (of 'fear') from the US

[28] The signs of estimates are not important because I do not constrain the correlation sign between latent variable and default premium when I extract the latent series, which can be either positively or negatively linked.

market. The yield spread and S&P 500 return are significant for about half of my sample countries. All three variables together are able to explain on average 46.62% of the variation of the latent series, with a maximum 72.88% for Israel and a minimum 12.66% for Greece, which is not surprising considering that the poor performance of the Greek market is largely caused by its internal problems within the Euro zone.

In the literature it is found that the spillover effect is stronger during the financial crisis. For example, Longstaff et al. (2011) use data from 2000 to 2010 and conclude that sovereign credit spreads are more related to the US market than they are to local measures; Fender et al. (2010) divide their data into two subsamples by the beginning of financial crisis and provide particular evidence that spreads are more strongly influenced by spillover effects during periods of market stress times. I run a 36-month rolling regression for each country and estimate the averaged adjusted R^2 in order to investigate the fluctuations of spillover effect, a higher adjusted R^2 suggests a stronger spillover effect from the US market. Figure 11 plots the results, the adjusted R^2 increases steadily and reaches its peak in 2009, when the CDS market is in most stress as depicted in Figure 7.

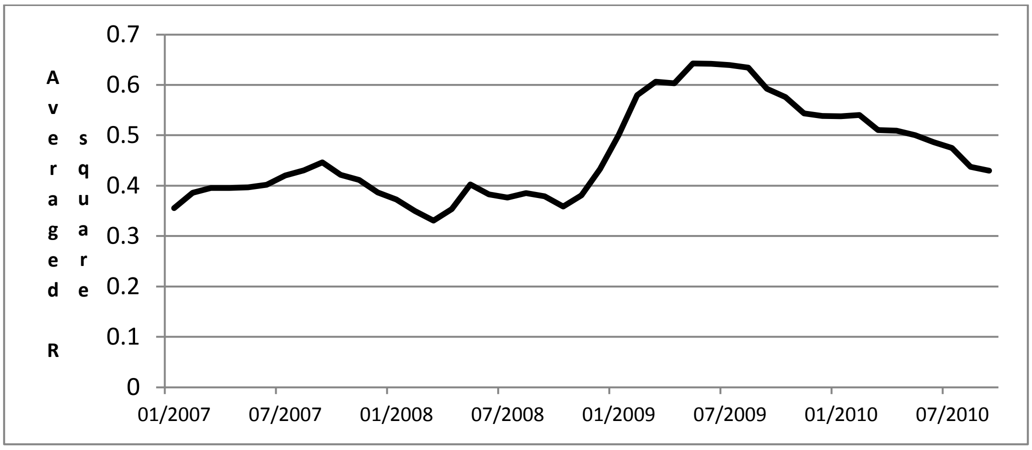
In summary, I find the US financial and economic variables explain a large portion of the latent series, suggesting a spillover effect from the US to other countries, the effect becomes stronger during stress periods.

Table 39. Spillover Effect from United States

	Estimates			t-statistics			Adjusted R^2	*N*
	VIX	Yield.diff	S&P 500	VIX	Yield.diff	S&P 500		81
Austria	0.0340***	0.0412	0.0497***	3.3679	0.9888	3.1531	0.3825	77
Brazil	0.0315**	-0.2022***	0.0151	2.5843	-4.0066	0.8247	0.1651	81
Chile	0.0592	0.0201	0.0426	5.8455	0.4798	2.6976	0.5980	76
Colombia	0.0170***	-0.2393	-0.0119***	1.6434	-5.6341	-0.7788	0.4609	81
Croatia	-0.0388***	-0.0226	-0.0340**	-3.8770	-0.5481	-2.1819	0.4041	79
Greece	0.0331***	-0.0630	0.0239	3.1081	-1.4285	1.4659	0.1266	80
Hungary	-0.0367***	-0.1084**	-0.0566***	-3.0374	-2.1684	-3.0105	0.4717	75
Israel	0.0203**	0.1703***	0.0023	2.4130	4.9004	0.1910	0.7288	81
Italy	0.0312**	0.1205**	0.0316	2.2438	2.1015	1.4562	0.3788	81
Japan	-0.0251***	-0.0412	-0.0157	-3.0414	-1.2087	-1.2188	0.3843	81
Korea	0.0301***	0.0969***	0.0343***	4.2529	3.3237	3.1089	0.6568	77
Malaysia	-0.0126*	-0.1529***	0.0118	-1.7095	-4.9925	1.0615	0.6776	81
Mexico	-0.0284***	-0.0418	-0.0281**	-3.7031	-1.3221	-2.3511	0.4581	78
Peru	-0.0233**	0.1871***	-0.0082	-2.1821	4.2474	-0.5096	0.2130	81
Philippines	-0.0613***	0.3615***	-0.0366*	-4.4708	6.3941	-1.7132	0.3309	81
Poland	-0.0711***	-0.0823*	-0.0933***	-6.6238	-1.8588	-5.5716	0.7104	76
Romania	0.0455***	0.1188**	0.0223	3.7304	2.3668	1.2375	0.6352	76
Russia	-0.0360***	-0.0392	-0.0053	-2.9628	-0.7847	-0.2936	0.4209	81
Slovak	0.0672***	-0.0263	0.0496***	6.7256	-0.6373	3.1829	0.5954	81
South Africa	0.0193*	0.0620	0.0108	1.8117	1.4118	0.6514	0.2521	81
Thailand	0.0307***	0.1344***	0.0174	4.1151	4.3634	1.4955	0.7170	76
Venezuela	0.0642***	-0.0506	0.0634***	5.4028	-1.0342	3.6177	0.4881	N

Note: Spillover effect from the United States market to other markets, three variables representing the US financial market are the VIX index (VIX), the spread between the Moody's 30-year US Baa corporate bond and the 6-month US Treasury bill rate (Yield.diff), and the S&P 500 return (S&P 500). Adjusted R^2 reports the adjusted R square value. *N* is the number of observations. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Figure 11. Averaged Adjusted R^2 of a Rolling Regression on Spillover Effect



Note: A 36-month rolling regression to investigate the fluctuations of spillover effect from the United States market to other markets, $X_{L,t} = \beta_0 + \beta_1 \text{VIX}_t + \beta_2 \text{YieldSpread}_t + \beta_3 \text{SP500}_t + \varepsilon_t$, three variables representing the US financial market are the VIX index (VIX), the spread between the Moody's 30-year US Baa corporate bond and the 6-month US Treasury bill rate (YieldSpread), and the S&P 500 return (SP500). The values in the plot are averaged adjust R^2 of all countries.

C5.6 Out-of-sample performance

A model with multiple variables may suffer over-fitting and may underperform a parsimonious candidate model. To determine if this is the case for my model, I conduct an out-of-sample analysis on a model with both macro factors and a latent variable (Full), against a model with a latent variable only (Latent)[29]. I test the performance of each year in my sample in order to capture better the ability of models under different market situations due to the financial crisis. I first fit parameters by using all data other than the given year and then use the fitted parameters to value the CDS spreads in that year. For example, to compare model out-of-sample performance for year 2004, I use

[29] A model with a latent variable only has the same structure as described earlier in the chapter, except that all parameters for the macro factors are restricted to zero.

data from January 2005 to September 2010 for parameter estimation and compute the model spreads for year 2004 with the estimated parameter set.

Out-of-sample RMSE is reported in Table 40 as a comparison criterion. Lower RMSE denotes better performance and is highlighted in bold. On average, the full model does a better job by generating a smaller RMSE than the latent model for 14 out of 22 countries, with an averaged cross-country 109 bps RMSE for the former model against 120 bps RMSE for the later. The full model tends to perform much better when the market is less volatile; specifically, it has a smaller out-of-sample RMSE for 15, 17, 20, and 17 countries for years 2004, 2005, 2006 and 2007, respectively, while the number decreases to 11, 13 and 8 for year 2008, 2009 and 2010, which may be explained by the following aspects: first, both inflation and real output values change suddenly after the breakout of crisis, as depicted in Figure 8. Consequently, the estimated parameters with data other than that year do not reflect well the unexpected change and perform relatively worse when pricing the CDS spreads for that year. Second, macro factors are less significant as determinants of sovereign spreads after the financial crisis, as a result, a model with the macro factors does not perform as better as it did. Fender et al. (2010) discover strong evidence that macroeconomic variables exert a significant impact on spreads only before the financial crisis. Nevertheless, the full model merely underperforms the latent model for the year 2010. Overall, I conclude that the performance of a model with only a latent factor can be improved by including macro factors. The improvement is more pronounced in normal circumstances before the crisis.

Table 40. Out-of-sample RMSE (in bps)

	2004		**2005**		**2006**		**2007**		**2008**		**2009**		**2010**		**All**		*N*
	Full	Latent	Full	Latent	Full	Latent	Full	Latent	Full	Latent	Full	Latent	Full	Latent	Full	Latent	81
Austria	**5.8523**	10.0056	**50.7721**	56.1145	**8.7584**	17.4438	**35.1792**	42.8995	**54.8483**	71.1519	**85.3201**	123.9174	95.4541	**87.1065**	**48.0264**	58.3770	77
Brazil	**383.4767**	407.6121	**96.9262**	97.1354	**176.4993**	188.9657	**250.6406**	256.5285	315.5121	**160.0280**	**107.8787**	144.8445	217.3438	**114.5995**	221.1825	**195.6734**	81
Chile	**48.2240**	48.2870	**8.2618**	10.7467	**7.9366**	18.2724	**15.7842**	16.2138	**47.1612**	169.4642	**171.9759**	190.9701	**17.0012**	18.3682	**45.1921**	67.4746	76
Colombia	**145.1516**	162.0097	**111.0365**	112.2484	198.5489	**176.4764**	249.2505	**216.3821**	234.6671	**171.9788**	**125.8350**	178.0857	**38.1510**	57.6915	157.5201	**153.5532**	81
Croatia	**37.0283**	88.9855	**67.4133**	104.6854	**81.5219**	129.6887	**23.5909**	99.4871	**194.1496**	212.9960	**207.6923**	284.6530	**184.6152**	218.5487	**113.7159**	162.7206	79
Greece	**13.0087**	163.2111	**21.1165**	100.5402	**103.2998**	127.7642	**28.4361**	109.0479	**42.8648**	61.0090	**52.9074**	220.5697	662.4246	**589.9964**	**132.0083**	196.0198	80
Hungary	**106.1308**	145.4113	**190.4678**	190.8454	**103.1498**	139.1322	**97.7781**	112.7286	**68.7606**	217.1347	231.2866	**154.0241**	421.9974	**371.5923**	**174.2244**	190.1241	75
Israel	45.3470	**8.1528**	**54.5960**	72.2819	**88.4575**	95.0824	15.4286	**11.8958**	**93.4080**	111.2634	111.3147	**62.2809**	**12.6241**	17.6222	60.1680	**54.0828**	81
Italy	**11.4703**	72.1479	58.8980	**5.1189**	**4.8547**	5.0116	**5.4673**	5.9989	**32.7305**	71.9789	**30.2187**	101.1773	59.2563	**54.8236**	**28.9851**	45.1796	81
Japan	**6.6620**	9.0240	**28.0462**	30.1392	**25.5173**	29.9082	**9.0363**	11.3581	13.4370	**12.6563**	**25.5167**	37.8084	38.1371	**34.0039**	**20.9075**	23.5569	81
Korea	**13.2005**	15.0589	19.8098	**18.1732**	**14.4543**	74.1760	**20.1893**	26.3855	**167.2408**	208.7580	**63.7254**	89.3666	141.5557	**51.3177**	**62.8823**	69.0337	77
Malaysia	**13.4392**	35.8693	**67.6922**	69.6008	**71.0793**	79.4404	88.2820	**18.2612**	44.9650	**38.8590**	**34.3463**	59.2292	79.4301	**26.3824**	57.0334	**46.8060**	81
Mexico	57.7088	**49.4862**	**43.1099**	56.8240	**20.0686**	87.4232	91.5370	**38.7144**	143.6631	**77.6085**	153.2396	**87.4419**	118.9984	**61.7156**	89.7608	**65.6020**	78
Peru	247.8267	**102.7735**	103.2771	**41.6707**	**40.0105**	48.8051	**42.3301**	45.4653	102.7942	**95.7804**	**132.1906**	175.7297	**53.7341**	65.9535	103.1662	**82.3112**	81
Philippines	82.6321	**78.4307**	**77.7026**	95.8387	**27.6073**	68.1602	**42.0201**	52.0809	**123.2573**	202.7259	98.8940	**94.8488**	127.3058	**74.0118**	**82.7742**	95.1567	81
Poland	**96.2403**	97.7945	99.0883	**96.2993**	**54.7520**	80.1345	**55.3787**	87.0220	40.6053	**35.1906**	76.2666	**42.7492**	36.4345	**26.4192**	**65.5380**	66.5156	76
Romania	**91.8344**	100.0800	**23.5645**	83.3114	**30.0767**	53.6316	**100.5876**	169.6364	124.2904	**108.7969**	128.2659	**116.7378**	242.5758	**102.1720**	105.8850	**104.9095**	76
Russia	142.2402	**89.5144**	**133.3085**	142.3989	**188.8322**	202.6091	**86.2599**	86.4636	**543.8823**	550.7824	548.4838	**142.4729**	140.8632	**60.3013**	254.8386	**182.0775**	81
Slovak	59.6015	**55.9320**	**6.7563**	10.1515	**5.1339**	12.6987	**40.7106**	49.5303	30.3628	**26.1546**	133.4495	**129.7588**	**32.2677**	46.9798	**44.0403**	47.3151	81
South Africa	**48.3211**	50.4608	**14.9280**	60.1563	**20.3784**	49.6846	35.4199	**29.0278**	187.0598	**118.2676**	**202.9697**	271.0796	29.4181	**25.0122**	**76.9279**	86.2413	81
Thailand	12.2231	**11.8810**	17.3200	**15.0327**	89.2587	**17.5689**	**68.3197**	71.1420	**133.9969**	173.3900	**95.8376**	157.5485	**14.3865**	37.6288	**61.6204**	69.1703	76

Venezuela	**54.0924**	441.6404	**66.0059**	395.6508	**91.3838**	520.6481	**85.7242**	401.0429	1468.0892	**1392.4334**	739.9702	**335.2766**	**288.1489**	541.3459	**399.0592**	575.4340	N

Note: Out-of-sample performance of a model with both macro factors and a latent variable (Full), against that of a model with a latent variable only (Latent). RMSE (root mean squared error) is reported as a comparison measure. I first fit parameters by using all data other than the given year, and then use the fitted parameters to value the CDS spreads in that year. Column “All” reports the average of each year’s RMSE. Lower RMSE denotes better performance and is highlighted in bold. *N* is the number of observations.

Chapter C6. Conclusion

This chapter values sovereign CDS spreads with observable macroeconomic variables and a latent variable under a multifactor affine framework, which allows macro variables to affect the dynamics of the term structure of sovereign credit risk by imposing no-arbitrage assumptions. Studying sovereign CDS spreads of 22 countries, I find that two macro factors (inflation and real output) are able to explain, on average, 23.06% of the variation of spreads, while the US financial variables explain 46.62% of the latent factor that cannot be captured by macro factors, consistent with the view that sovereign markets are impacted by spillovers from the United States economy to other regions of the world. Furthermore, I find that incorporating macro factors in a sovereign CDS term structure model improves the out-of-sample performance.

Appendix C.A Extended Kalman Filter

In this appendix I describe the extended Kalman filter technique and maximum log-likelihood method for the estimation of CDS pricing related parameters. Let $\varpi_t = (\varpi_{t1}, \dots, \varpi_{tn})$ be the CDS spreads with maturity *t*1 to *t*n, and *Xt* be the three factors that drive the CDS spreads. We then have the following measurement and transition equations:

$$\varpi_t = F(X_t) + \varepsilon_t, \mathrm{E}[\varepsilon_t {\varepsilon_t}^{\mathrm{T}}] = \Sigma \qquad \text{(A1)}$$

$$X_t = \mu + \Gamma X_{t-1} + \upsilon_t, \mathrm{E}[\upsilon_t {\upsilon_t}^{\mathrm{T}}] = \Omega$$

where *F*(.) maps the factors into CDS spreads as in equation (11), Σ and Ω are matrices for the variances of the errors of CDS yields and three factors, respectively. μ and Γ are defined as in equation (6):

$$\mu = -\int_{t-\Delta t}^{t} \mathrm{expm}(-k^Q(t-s))\gamma_0 ds \qquad \text{(A2)}$$

$$\Gamma = \mathrm{expm}(-k^Q \Delta t)$$

$$\Omega = \int_{t-\Delta t}^{t} \mathrm{expm}(-k^Q(t-s))\mathrm{expm}(-k^Q(t-s))^{\mathrm{T}} ds$$

We can then apply typical Kalman filter method to estimate the parameters by

Step 1: forecasting the measurement equation $\widehat{\varpi_t}$ in (A1) given initial values;

Step 2: updating the inference about the factors incorporating the prediction error $\epsilon_t = \widehat{\varpi_t} - \varpi_t$;

Step 3: forecasting the factors of the next time period conditioning on the updated values of the previous period;

Step 4: calculating the log-likelihood function by assuming Σ in equation (A1) is Gaussian and maximizing the log-likelihood:

$$l_t = -\frac{n}{2}\log(2\pi) - \frac{1}{2}\log(|\mathrm{var}(\widehat{\varpi_{\mathrm{t}}})|) - \frac{1}{2}\epsilon_t^{\mathrm{T}}\mathrm{var}(\widehat{\varpi_{\mathrm{t}}})^{-1}\epsilon_t \quad \text{(A3)}$$

where n is the number of observations.

Appendix C.B Sovereign CDS Valuation

In this appendix I derive the valuation formula for sovereign CDS spread for equation (11). Begin with a stochastic differential equation for X_t as

$$dX_t = \mu(X_t)dt + \sigma(X_t)dW_t \tag{B1}$$

Here W_t is a vector of standard Brownian motion, $\mu(X_t)$ and $\sigma(X_t)$ are the drift and diffusion terms defined as

$$\mu(X_t) = K_0 + K_1 X_t, (\sigma(X_t)\sigma(X_t)^{\mathrm{T}})_{ij} = (H_0)_{ij} + (H_1)_{ij} X_t$$

where K_0, K_1, H_0 and H_1 are coefficients. Duffie et al. (2000) prove under technical regularity conditions that the solution for the conditional expectation of an asset F

$$F(X_t, t, T) = E[\exp(-\int_t^T R(X_s)ds)] \tag{B2}$$

is given by

$$F(X_t, t, T) = \exp(\alpha + \beta X_t) \tag{B3}$$

where $R(X_t) = \rho_0 + \rho_1 X_t, , \rho_0$ and ρ_1 are coefficients determining the payoff structure. β and α satisfy the ordinary differential equations (ODEs)

$$\beta' = \rho_1 - {K_1}^{\mathrm{T}}\beta - \tfrac{1}{2}\beta^{\mathrm{T}} H_1 \beta \tag{B4}$$

$$\alpha' = \rho_0 - K_0\beta - \frac{1}{2}\beta^{\mathrm{T}} H_0 \beta$$

subject to boundary conditions $\beta = \alpha = 0$. Standard linear transformation leads to our equation (14) when $dX_t = k^Q(\theta^Q - X_t)dt + dW_t^Q$.

The derivation for equation (16) is more involved. Suppose

$$F(v, X_t, t, T) = E[vX_T \exp(-\int_t^T R(X_s)ds)] \tag{B5}$$

v is another coefficient in the payoff structure. Duffie et al. (2000) show that this type of extended transform has a solution

$$F(v, X_t, t, T) = F(X_t, t, T)(A + BX_t) \tag{B6}$$

where $F(X_t, t, T)$ is as in equation (B3), and where B and A satisfy the ODEs

$$B' = -K_1{}^{\mathrm{T}}B - \beta^{\mathrm{T}}H_1B \tag{B7}$$

$$A' = -K_0\beta - \beta^{\mathrm{T}}H_0B$$

β is calculated as in equation (B4), with the boundary conditions $B = v,\ A = 0$. Equation (16) is then derived by linear transformation.

Appendix C.C Tables

Appendix Table 41. Macro Factor Loadings for Macroeconomic Variables

	Austria		Brazil		Chile		Colombia		Croatia		Greece	
	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output
Loading												
CPI	0.9756***		0.5009***		0.4151***		0.7452***		0.154239		0.9461***	
PPI	1.1899***		0.8864***		1.0864***		0.5023***		NA		1.1179***	
PCE	0.5346**		NA		0.7857***		0.3405**		0.8995***		0.7242***	
GDP	0.7169***		0.1669		0.6331***		NA		0.8976***		0.4370**	
IP		0.8417***		1.2263***		0.3861***		NA		NA		0.4344***
Unemploy		-0.5081***		-0.6461*		-0.9336		-1.2939		-0.3845***		-0.6684***
Real.PCE		0.4761**		0.9095		0.6460***		NA		0.2555***		0.5879***
Real.GDP		0.7838***		1.2716***		0.9205***		NA		0.2779***		0.5330***
t-statistics												
CPI	8.8976		5.3835		3.4964		12.0911		1.3228		9.2375	
PPI	12.3134		12.1360		12.1196		6.6607				12.2142	
PCE	2.5198				5.1378		2.5422		5.8510		4.0855	
GDP	3.6734		0.9970		3.6600				5.8447		2.1319	
IP		8.2843		8.1864		3.8778						5.6267
Unemploy		-3.5887		-1.9492		-0.8419		-1.0151		-11.5824		-3.2248
Real.PCE		2.5601		0.3873		4.8294				5.9745		3.4924
Real.GDP		8.2698		7.1789		12.6999				5.0193		5.5182

Appendix Table 41. Macro Factor Loadings for Macroeconomic Variables (*continued*)

	Hungary		Israel		Italy		Japan		Korea		Malaysia	
	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output
Loading												
CPI	1.1224***		0.2292		0.6868***		0.7433***		0.9162***		0.5491***	
PPI	0.3639***		1.2313***		0.8747***		0.8386***		1.0126***		1.0543***	
PCE	0.4767**		0.7119***		0.7265***		0.3863***		-0.0953		0.7549***	
GDP	0.027458		NA		0.6206***		0.3313**		0.1004284		0.8386***	
IP		0.9990***		0.5162***		0.9381***		0.9225***		1.3084***		1.2498***
Unemploy		-0.5963***		-0.7515***		-0.5070***		-0.4929***		-0.2977**		-0.2315
Real.PCE		0.7563		0.3880***		0.8428		0.6969**		1.0106		0.9359
Real.GDP		0.8542***		0.9813***		0.9192***		0.8234***		1.3179***		1.2596***
t-statistics												
CPI	12.1987		1.6159		8.4208		10.1330		10.4684		4.8946	
PPI	2.9763		11.8900		12.4765		12.5126		12.4031		12.0703	
PCE	2.5100		3.3679		6.5438		2.6817		-0.4944		4.6874	
GDP	0.1329				4.8152		2.2421		0.5200		5.7005	
IP		8.0187		6.7325		8.8362		12.3347		7.0652		6.4410
Unemploy		-2.7234		-3.4018		-3.3382		-3.6575		-2.4704		-1.3914
Real.PCE		1.4221		2.6638		1.1557		2.1527		0.0495		0.2598
Real.GDP		6.2385		12.1682		8.3814		9.3144		6.9704		6.0330

Appendix Table 41. Macro Factor Loadings for Macroeconomic Variables (*continued*)

	Mexico		Peru		Philippines		Poland		Romania		Russia	
	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output
Loading												
CPI	0.5788***		0.6652***		0.9426***		0.4610**		-0.0759		0.2230*	
PPI	1.2649***		0.8425***		0.5169***		1.2700***		0.9196***		1.1145***	
PCE	0.4168*		0.4721***		0.1227		0.5322		0.6665***		0.8710***	
GDP	0.3148		NA		0.4768***		0.0191		0.6902***		0.9055***	
IP		0.9535***		1.0308***		1.6997***		0.1027**		0.1380**		0.7929***
Unemploy		-0.7725*		-0.0988		-0.4124		-0.4253***		-0.5213***		-0.8645
Real.PCE		0.9302		NA		0.4018		0.2822***		0.4175***		0.6317**
Real.GDP		0.9492***		NA		1.0810***		0.3140***		0.4572***		0.7532***
t-statistics												
CPI	4.3280		8.3382		12.3582		2.6139		-0.7190		1.7619	
PPI	12.3190		12.2453		5.3316		2.9236		12.0277		11.9377	
PCE	1.8494		3.3982		0.6986		1.6137		4.6721		5.5508	
GDP	1.3644				3.0544		1.4332		5.0097		5.9697	
IP		9.0788		5.1326		6.6655		2.2035		2.3507		8.8044
Unemploy		-1.9055		-0.7532		-1.1102		-10.7760		-7.9013		-1.3639
Real.PCE		0.6053				1.1443		5.5832		5.4289		2.3453
Real.GDP		8.8990				3.7498		5.3000		7.7284		7.3599

Appendix Table 41. Macro Factor Loadings for Macroeconomic Variables (*continued*)

	Slovak		South Africa		Thailand		Venezuela	
	Inflation	Real output	Inflation	Real output	Inflation	Real output	Inflation	Real output
Loading								
CPI	0.4647***		0.4869***		1.2710***		0.5717***	
PPI	0.7726***		0.8816***		1.1296***		0.7112***	
PCE	0.6326***		0.3675**		0.7413***		0.0018	
GDP	0.3774***		0.6174***		0.4462*		0.1626**	
IP		0.0237		0.6832***		1.4426***		0.4958***
Unemploy		-0.5262***		-0.7391***		-1.0071		-0.5420***
Real.PCE		0.4464***		0.7624		1.1340		0.5772***
Real.GDP		0.3425***		0.8295***		1.4568***		0.5972***
t-statistics								
CPI	5.9152		5.3698		12.2781		4.7253	
PPI	12.5347		12.4361		10.0100		4.1306	
PCE	7.0665		2.4586		3.3337		1.3272	
GDP	3.0106		5.0927		1.8167		2.1186	
IP		0.4050		4.7565		8.2991		4.7537
Unemploy		-7.9645		-5.1668		-0.0430		-3.1333
Real.PCE		5.7307		1.4102		0.6221		2.7342
Real.GDP		4.2409		12.7122		8.4000		5.0861

Notes: Factor loadings matrix H and associated t-statistics for macro factors extraction, $Y_t = \mathrm{H}X_{m,t} + \varepsilon_t$, where the macroeconomic variables in the first column are CPI, PPI, PCE, GDP, IP, Unemployment, Real PCE and Real GDP. "*", "**", "***" represent 10%, 5% and 1%

significance level, respectively. There are few countries that I cannot get enough data for the macroeconomic variable, in that case, I estimate macro factors without that variable and denote its loading as “NA”.

Appendix Table 42. Market Prices of Risk

	Austria				Brazil				Chile			
	k			Theta (Θ)	k			Theta (Θ)	k			Theta (Θ)
Estimates												
Inflation	0.7092***	0.0000	0.0000	22.6381***	0.0905***	0.0000	0.0000	-8.5432***	0.0954***	0.0000	0.0000	-36.1672***
Real output	0.2192***	0.0000	0.0000	12.3049***	0.6625***	0.0026	0.0000	3.5516***	-0.0520***	0.0009	0.0000	23.6183***
Latent	0.0000	0.0000	0.0023***	41.7649***	0.0000	0.0000	0.0017	-2.4801***	0.0000	0.0000	0.0000	-44.5689***
t-statistics												
Inflation	32.8297	-	-	15.5773	3.9811	-	-	-174.3028	34.1852	-	-	-14.2977
Real output	37.3586	0.0177	-	41.0805	15.7150	0.5148	-	104.7901	-33.4906	0.3807	-	14.9980
Latent	-	-	11.7493	68.1507	-	-	0.7156	-63.0472	-	-	0.7406	-28.2696
	Colombia				Croatia				Greece			
	k			Theta (Θ)	k			Theta (Θ)	k			Theta (Θ)
Estimates												
Inflation	0.0762***	0.0000	0.0000	11.5274***	0.0000	0.0000	0.0000	68.1455***	0.0304***	0.0000	0.0000	-77.9451***
Real output	0.6915***	0.4804***	0.0000	-21.6594***	0.1066***	0.0000	0.0000	-147.6720***	-0.1004***	0.1120***	0.0000	-83.6446***
Latent	0.0000	0.0000	0.0043***	-4.0356***	0.0000	0.0000	0.0057	7.2432***	0.0000	0.0000	0.1151***	1.1992
t-statistics												
Inflation	5.4905	-	-	14.0024	0.0166	-	-	10.8784	5.3290	-	-	-63.8879
Real output	8.5538	9.6098	-	-18.1075	3.7958	0.0362	-	-141.9177	-7.7592	13.5788	-	-146.0296
Latent	-	-	0.7160	-14.3876	-	-	0.9197	11.4261	-	-	11.5362	1.1458

Appendix Table 42. Market Prices of Risk (*continued*)

	Hungary				Israel				Italy			
	k			Theta (Θ)	k			Theta (Θ)	k			Theta (Θ)
Estimates												
Inflation	0.0187	0.0000	0.0000	-0.9130***	0.1467***	0.0000	0.0000	-17.2837***	0.0295**	0.0000	0.0000	-20.9218***
Real output	0.0325	0.0375***	0.0000	-4.3591***	0.0271	0.0000	0.0000	-8.4117***	-1.7496***	0.9736***	0.0000	2.0538***
Latent	0.0000	0.0000	0.0230***	-5.5626***	0.0000	0.0000	0.0005	2.5691***	0.0000	0.0000	0.0013	30.3279***
t-statistics												
Inflation	0.1884	-	-	-18.5614	4.9329	-	-	-276.8776	2.5908	-	-	-78.0847
Real output	1.5353	3.9253	-	-44.5957	1.5055	0.0021	-	-150.4726	-24.1576	14.6142	-	10.2861
Latent	-	-	5.7721	-84.3862	-	-	0.7096	42.7027	-	-	1.0310	33.8596
	Japan				Korea				Malaysia			
	k			Theta (Θ)	k			Theta (Θ)	k			Theta (Θ)
Estimates												
Inflation	0.0077***	0.0000	0.0000	-29.1813***	0.2883***	0.0000	0.0000	4.2908***	0.3814***	0.0000	0.0000	1.0385***
Real output	-1.0264***	0.4089***	0.0000	-77.3751***	0.1935***	0.0634***	0.0000	-11.7840***	-0.0570***	0.0510***	0.0000	-8.2868***
Latent	0.0000	0.0000	0.0013	-5.4849***	0.0000	0.0000	0.0015	0.9608***	0.0000	0.0000	0.0006	3.4484***
t-statistics												
Inflation	3.2376	-	-	-25.6739	18.5575	-	-	46.2129	4.9761	-	-	59.4769
Real output	-10.3373	9.7931	-	-27.7066	10.7081	15.4455	-	-58.4401	-3.7781	17.4037	-	-32.0366
Latent	-	-	0.7069	-9.9911	-	-	0.7929	22.4295	-	-	0.7074	69.4484

Appendix Table 42. Market Prices of Risk (*continued*)

	Mexico				Peru				Philippines			
	k			Theta (Θ)	k			Theta (Θ)	k			Theta (Θ)
Estimates												
Inflation	0.3059***	0.0000	0.0000	0.2284***	0.0067	0.0000	0.0000	-9.4428***	0.0061	0.0000	0.0000	-3.6472***
Real output	0.4065***	0.0078***	0.0000	-129.1018***	0.1706***	0.0571	0.0000	-6.5680***	0.4665***	0.1217***	0.0000	-8.3986***
Latent	0.0000	0.0000	0.0019	1.9994***	0.0000	0.0000	0.0014	0.9032***	0.0000	0.0000	0.0021	1.2031***
t-statistics												
Inflation	21.5832	-	-	12.6564	0.1513	-	-	-99.8328	0.1502	-	-	-25.0616
Real output	19.4723	28.3584	-	-312.4229	2.9358	1.0692	-	-42.9336	5.1253	3.3385	-	-39.6486
Latent	-	-	0.7399	30.2964	-	-	0.7076	4.5878	-	-	0.7190	7.1298

	Poland				Romania				Russia			
	k			Theta (Θ)	k			Theta (Θ)	k			Theta (Θ)
Estimates												
Inflation	0.1894***	0.0000	0.0000	13.9816***	1.0012***	0.0000	0.0000	-7.5132***	0.0220***	0.0000	0.0000	28.9354***
Real output	0.7257***	0.9990***	0.0000	-10.7242***	-0.2695**	0.0856***	0.0000	-14.6602***	0.1229***	0.0903***	0.0000	-44.4702***
Latent	0.0000	0.0000	0.0007	0.3499***	0.0000	0.0000	0.0073***	4.7345***	0.0000	0.0000	0.1274***	-0.5337**
t-statistics												
Inflation	5.9099	-	-	241.4094	18.5551	-	-	-182.5703	3.0567	-	-	17.0217
Real output	6.1718	28.6601	-	-126.0252	-2.3960	7.9899	-	-196.7815	7.4240	8.3436	-	-20.0951
Latent	-	-	0.7170	7.1851	-	-	2.6631	93.2027	-	-	8.3560	-2.4024

Appendix Table 42. Market Prices of Risk (*continued*)

	Slovak				South Africa				Thailand			
	k			Theta (Θ)	k			Theta (Θ)	k			Theta (Θ)
Estimates												
Inflation	0.5870***	0.0000	0.0000	1.1211***	0.0725***	0.0000	0.0000	30.9947***	0.0963***	0.0000	0.0000	-5.7710***
Real output	-0.6929***	0.0186***	0.0000	-52.2557***	0.0033	0.0000	0.0000	4.5242***	0.1081	0.0002***	0.0000	0.2359***
Latent	0.0000	0.0000	0.0005***	2.4054***	0.0000	0.0000	0.0411***	-2.9576	0.0000	0.0000	0.0005***	-2.3600***
t-statistics												
Inflation	26.5397	-	-	17.4264	3.3861	-	-	181.9872	4.0914	-	-	-32.4977
Real output	-18.4738	13.4963	-	-40.0525	0.3399	0.0026	-	22.1983	16.3341	0.0111	-	8.9468
Latent	-	-	0.7097	36.3605	-	-	2.9384	-13.1176	-	-	0.7087	-87.4794

	Venezuela			
	k			Theta (Θ)
Estimates				
Inflation	0.2772***	0.0000	0.0000	14.2634***
Real output	0.4128***	0.2169***	0.0000	-15.6805***
Latent	0.0000	0.0000	0.1141***	0.8497***
t-statistics				
Inflation	9.0182	-	-	41.3954
Real output	13.0091	8.3148	-	-81.6072
Latent	-	-	14.8467	20.7598

Notes: K and Θ matrix estimates for Greece, $dX_t = k^Q(\theta^Q - X_t)dt + dW_t^Q$. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Appendix Table 43. Instantaneous Credit Spread

	Austria		Brazil		Chile		Colombia		Croatia		Greece	
	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic
Intercept (α)	0.0021***	7.5770	0.0086***	8.3887	0.0029***	5.7299	0.0082***	10.5562	0.0082***	11.0758	0.0120***	7.0774
Inflation	0.0010**	2.1785	0.0029***	3.2155	-0.0014*	-1.8220	0.0020***	3.4491	-0.0109***	-9.6757	0.0114***	5.4957
Real output	-0.0029***	-8.9683	-0.0029**	-2.1676	-0.0011	-1.6432	-0.0046***	-3.4687	0.0007	1.5307	-0.0163***	-13.0276
Latent	0.0068***	13.5851	-0.0233***	-13.3964	0.0090***	18.7503	-0.0160***	-12.2868	-0.0155***	-18.4512	0.0399***	9.5387
	Hungary		Israel		Italy		Japan		Korea		Malaysia	
	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic
Intercept (α)	0.0095***	8.3180	0.0038***	9.1105	0.0032***	5.8381	0.0009***	7.4841	0.0060***	7.8446	0.0039***	9.2712
Inflation	-0.0032**	-2.4110	-0.0010	-1.3650	-0.0015**	-2.0961	-0.0004***	-3.7050	0.0014*	1.8403	0.0007	0.9765
Real output	-0.0103***	-8.3415	-0.0019***	-4.0830	0.0000	0.0228	-0.0008***	-6.1563	-0.0081***	-7.7523	-0.0058***	-6.3534
Latent	-0.0179***	-19.2857	0.0084***	16.3589	0.0078***	13.0759	-0.0038***	-12.7213	0.0170***	23.0232	-0.0091***	-13.9976

Appendix Table 43. Instantaneous Credit Spread (*continued*)

	Mexico		Peru		Philippines		Poland		Romania		Russia	
	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic
Intercept (α)	0.0059***	9.7098	0.0075***	11.0367	0.0133***	12.5651	0.0042***	6.1541	0.0126***	7.5951	0.0135***	6.7284
Inflation	0.0010	1.3486	0.0030***	4.7818	0.0031***	2.9211	0.0002	0.2366	0.0001	0.0697	-0.0026	-0.8129
Real output	-0.0054***	-8.9637	-0.0053***	-5.8938	-0.0056***	-2.7813	-0.0014***	-4.8582	-0.0054***	-5.0371	-0.0113***	-4.5644
Latent	-0.0155***	-20.3808	0.0187***	12.5052	0.0181***	14.8152	-0.0098***	-26.1297	0.0225***	8.5366	-0.0345***	-13.3642

	Slovak		South Africa		Thailand		Venezuela	
	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic	Estimates	t-statistic
Intercept (α)	0.0024***	6.0327	0.0067***	9.3763	0.0046***	9.1491	0.0618***	9.8255
Inflation	0.0005	0.7711	0.0038***	5.3796	-0.0010	-1.3901	0.0147***	2.8755
Real output	-0.0010**	-2.3650	-0.0071***	-10.5517	-0.0046***	-5.2114	-0.0248***	-5.6847
Latent	0.0069***	14.5057	0.0152***	13.1150	0.0095***	12.4681	0.1146***	23.0707

Notes: The intercept and factor loadings for the instantaneous credit spread function, $\lambda(X_t) = a + b^{\mathrm{T}} X_t$. “*”, “**”, “***” represent 10%, 5% and 1% significance level, respectively.

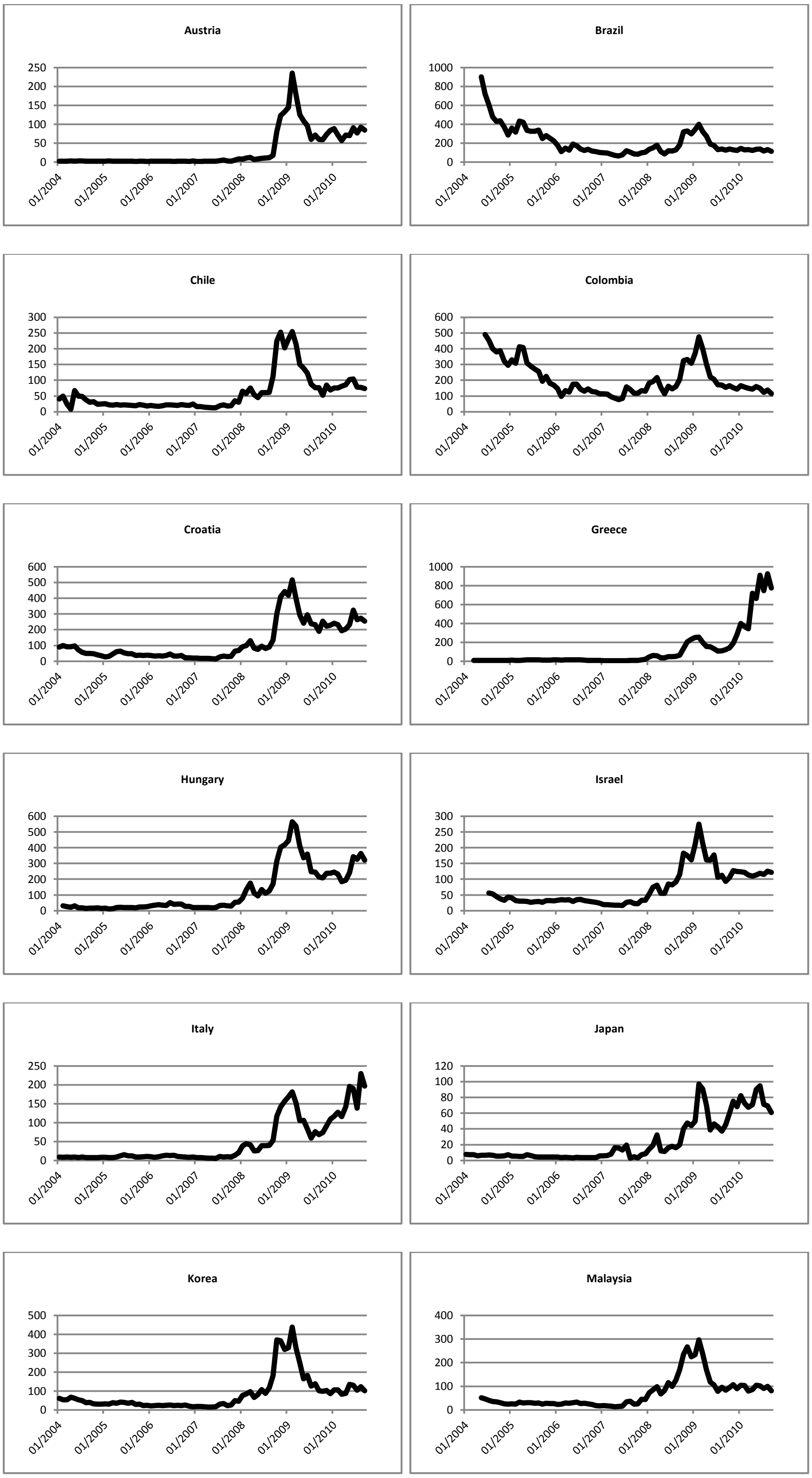
Appendix Table 44. Spread level test

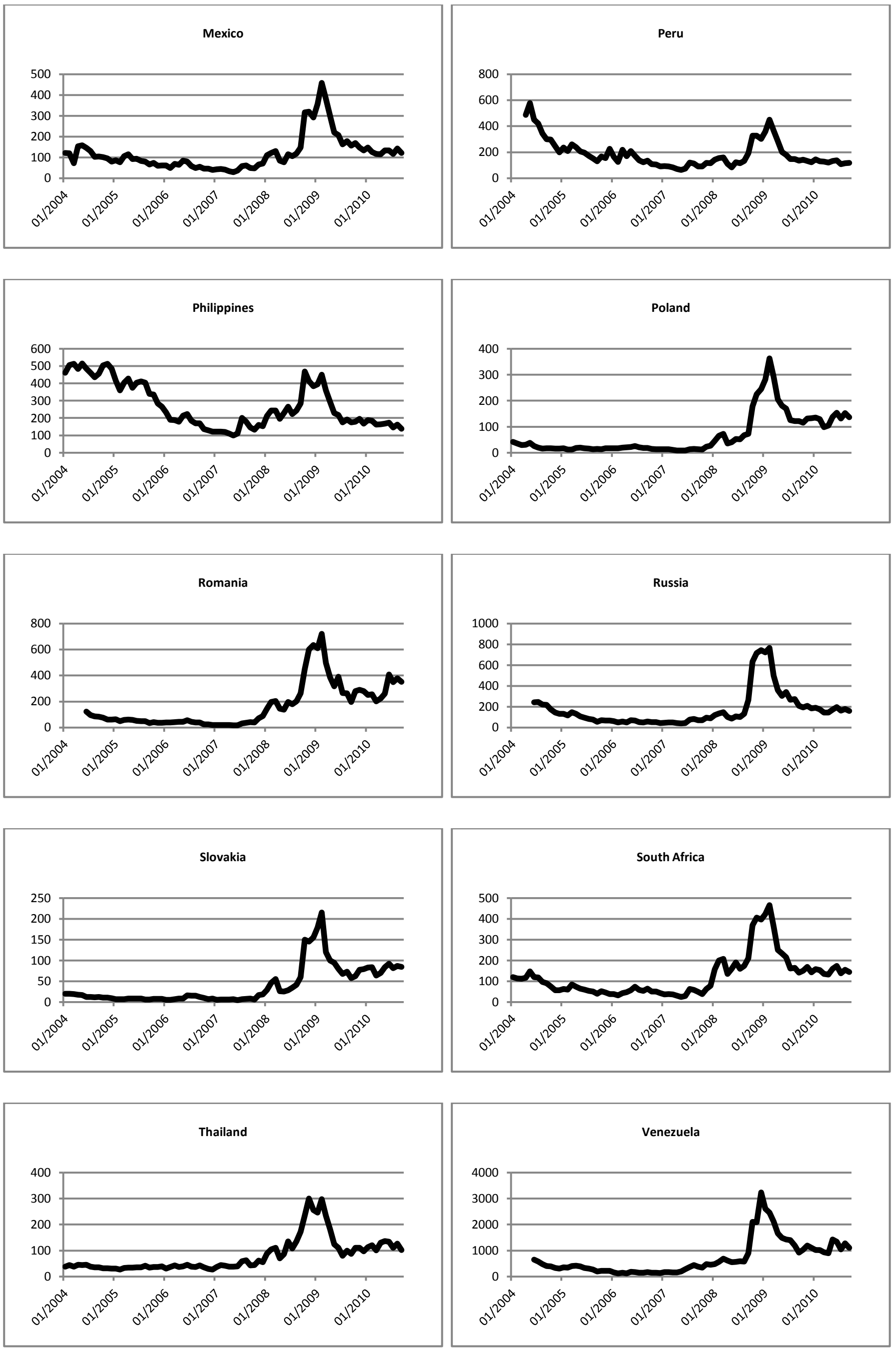
	β_0	β_1	β_1=1	AdjR^2
Austria	0.0001	1.0254***	0.5401	0.8575
Brazil	-0.0009	0.9887***	-0.1771	0.7608
Chile	0.0004	0.9333***	-1.3730	0.8233
Colombia	-0.0010	1.0627***	0.6866	0.6448
Croatia	0.0011	0.9172***	-2.0789	0.8703
Greece	0.0004	0.9886***	-0.3107	0.9041
Hungary	0.0007	0.9463***	-1.4269	0.8899
Israel	0.0001	1.0010***	0.0228	0.8681
Italy	-0.0001	1.0779***	1.5766	0.8573
Japan	-0.0001	1.1075***	1.1926	0.6548
Korea	0.0006	0.9206***	-1.7940	0.8453
Malaysia	-0.0003	1.0763***	1.4004	0.8385
Mexico	0.0010	0.9268***	-1.6378	0.8446
Peru	-0.0002	1.0030***	0.0536	0.8111
Philippines	-0.0006	1.0047***	0.1085	0.8709
Poland	-0.0002	1.0261***	0.6553	0.8937
Romania	0.0011	0.9343***	-1.7022	0.8876
Russia	0.0014	0.8969***	-2.4972	0.8641
Slovakia	0.0003	0.9635***	-0.7218	0.8213
South Africa	0.0007	0.9488***	-1.0646	0.8306
Thailand	-0.0002	1.0419***	0.8353	0.8451
Venezuela	0.0030	0.9417***	-1.3586	0.8667

Note: The table provides the coefficient estimates of the regression $CDS_{i,t}^{obs} = \beta_{0,i} + \beta_{1,i}CDS_{i,t}^{m} + \varepsilon_{i,t}$, where $CDS_{i,t}^{obs}$ is the observed CDS spread for country i at time t, and $CDS_{i,t}^{m}$ is the CDS spread estimated by our model. Column $\beta_1 = 1$ reports the t-statistics of the null hypothesis that the slope estimate β_1 equals to one. The last column shows the adjusted R^2 of regression. "*", "**", "***" represent 10%, 5% and 1% significance level, respectively.

Appendix C.D Figures

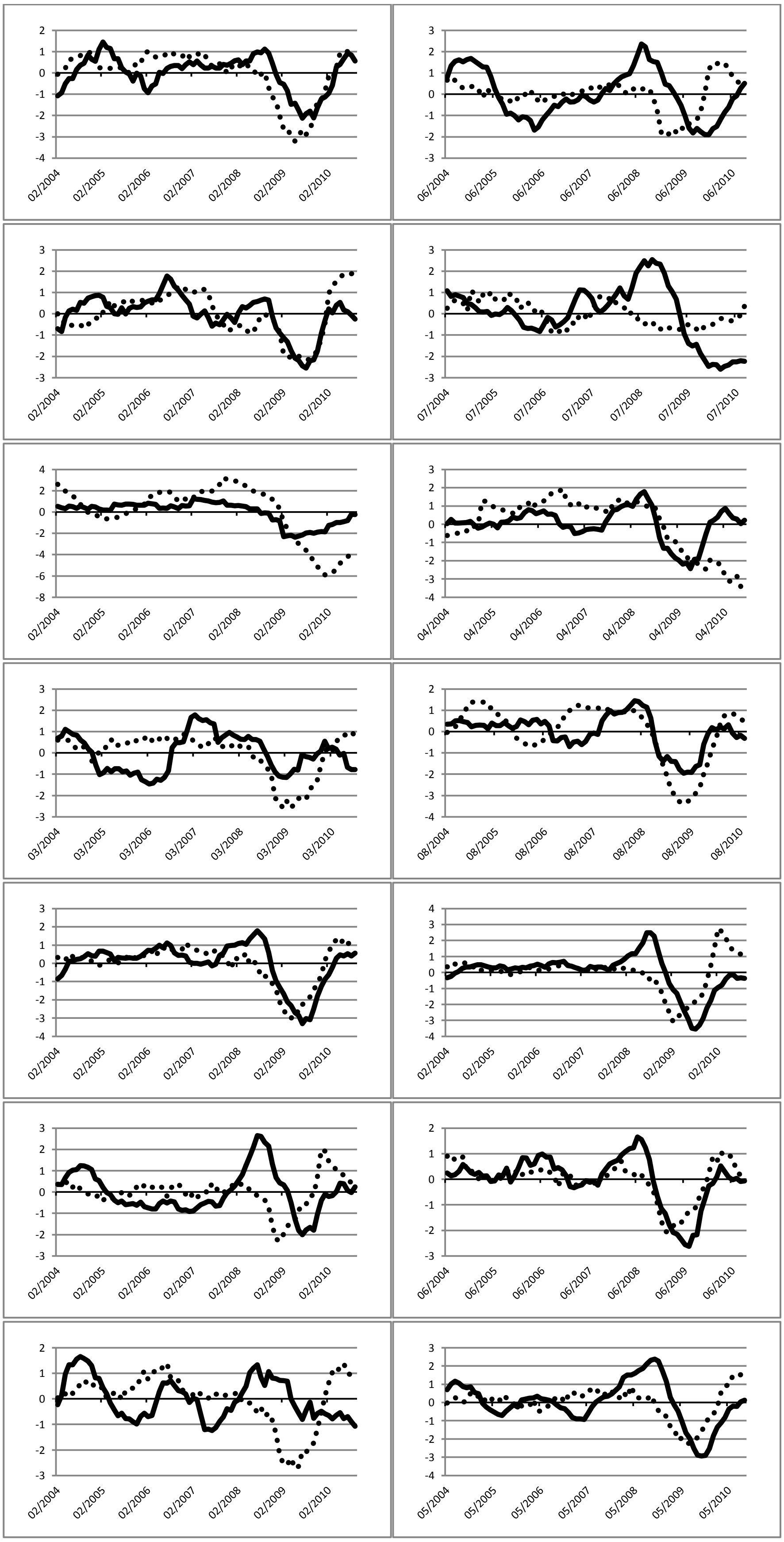
Appendix Figure 12. Time Series Plot of All Sovereign CDS Spreads (bps)

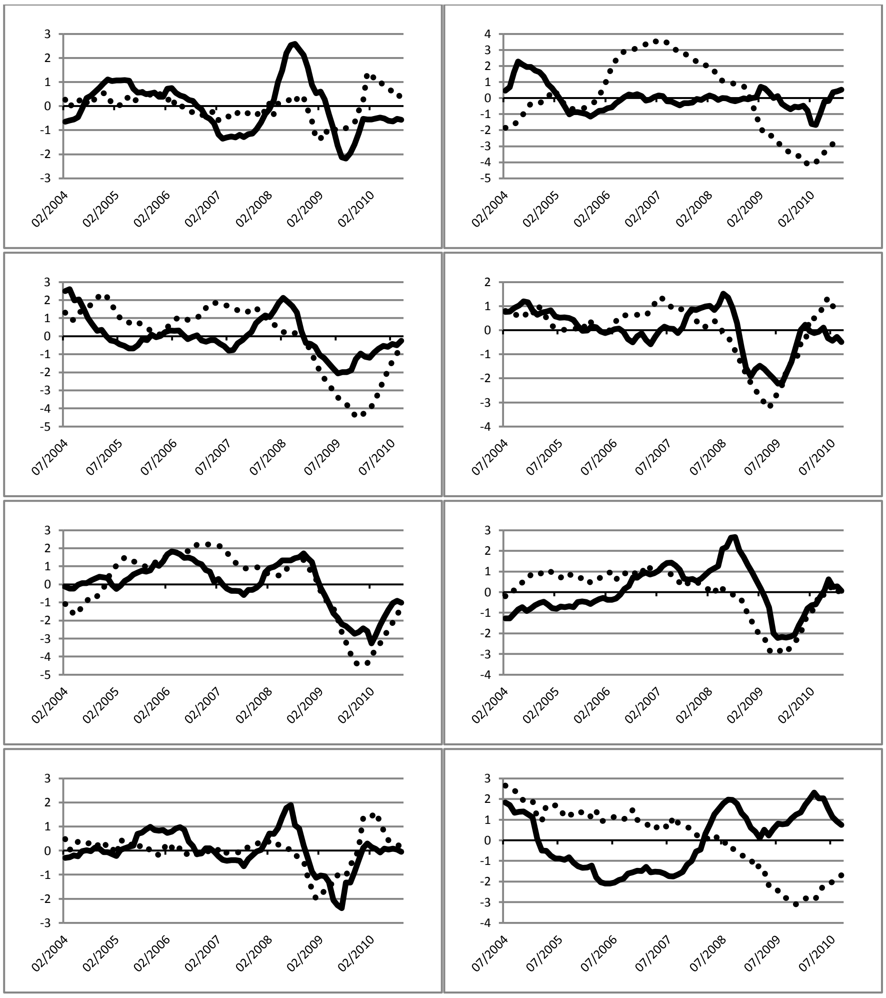




Notes: Plot of sovereign CDS spreads for all countries in my sample. Y axis is sovereign CDS spreads in bps.

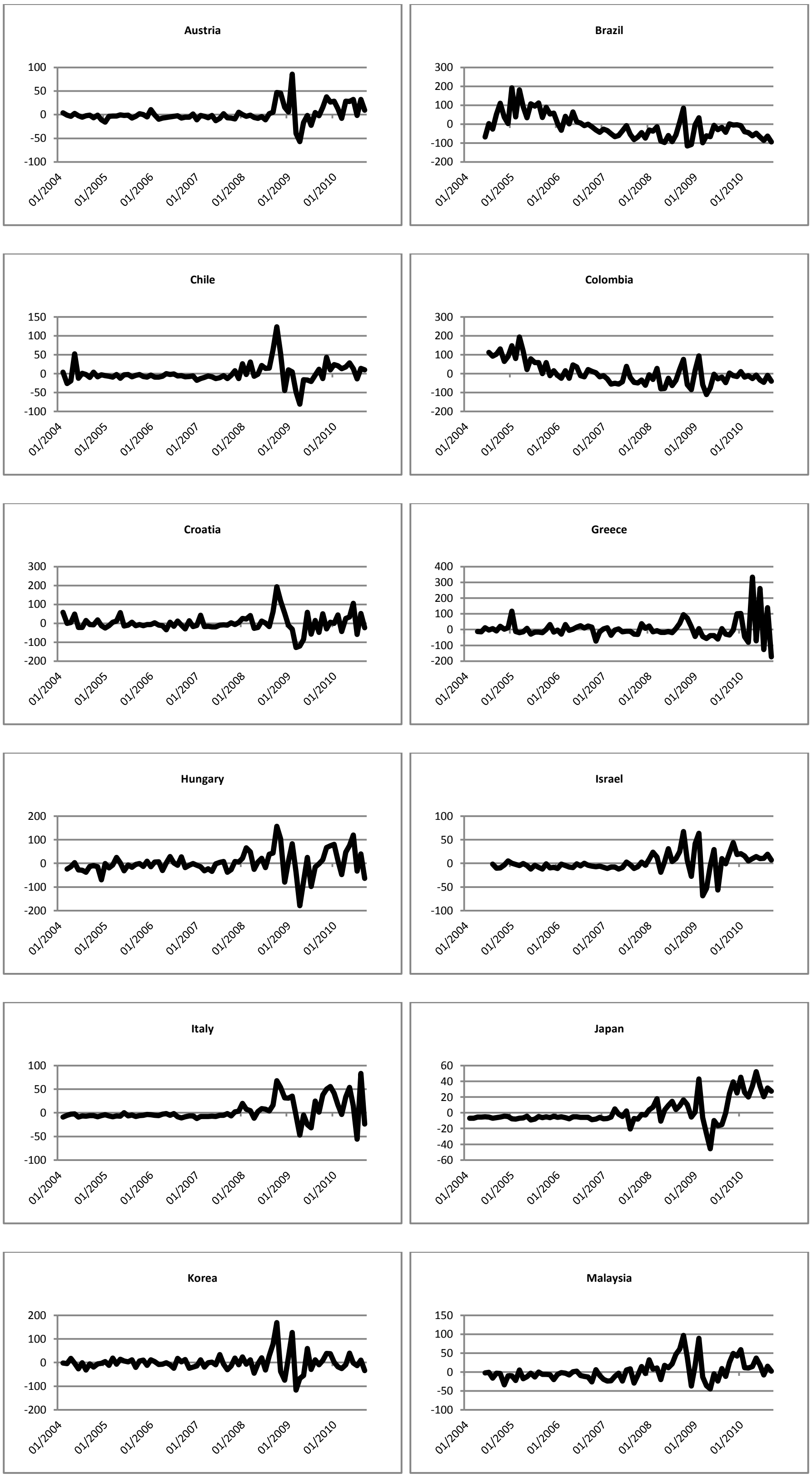
Appendix Figure 13. Time Series Plot of Extracted Macro Factors

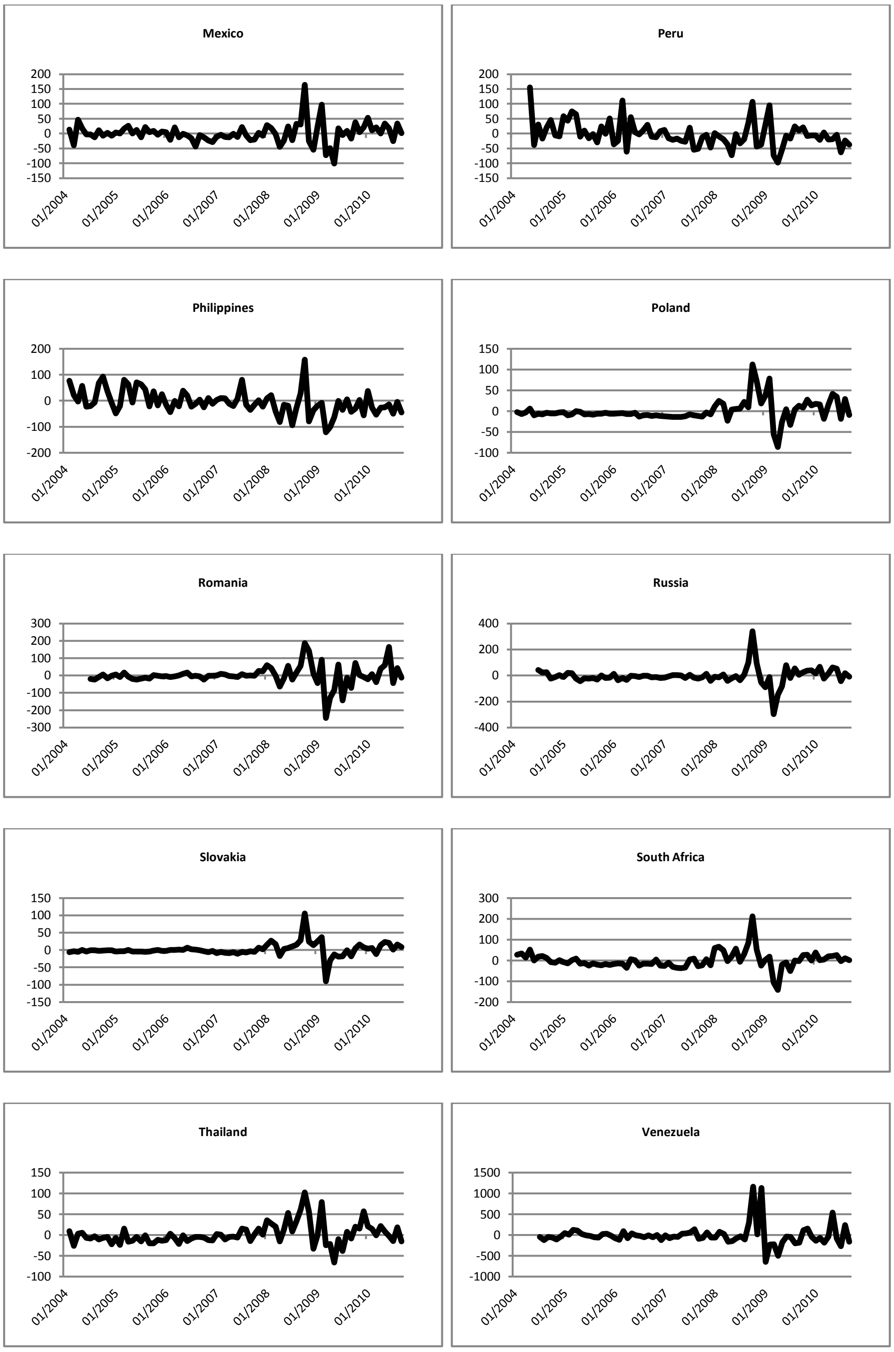




Notes: Plots of the extracted inflation (in line) and real output (in dot) factors for all countries. Plots from the top left to the bottom right are for country Austria, Brazil, Chile, Colombia, Croatia, Greece, Hungary, Israel, Italy, Japan, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russia, Slovak, South Africa, Thailand and Venezuela, respectively. Y axis is the standardized value.

Appendix Figure 14. Time Series Plot of Model Pricing Errors (bps)





Notes: Plot of model pricing errors of 5-year sovereign CDS. Pricing errors are defined as the difference between model implied spreads and market observed spreads. Y axis is pricing errors in bps.

Part D: Conclusion and Further Research

Motivated by 1) the increasing default loss rate after the beginning of the financial crisis in 2007 and 2) the insufficiency of existing models of default to explain default spreads, this thesis aims to contribute to the literature by finding the determinants of corporate and sovereign CDS spreads using recent data covering both before and after the financial crisis from 2004 to 2010.

Three pricing factors affecting the valuation of CDS are interest rate, credit spread and liquidity spread. In Part A I review several models on those pricing factors, the dynamics researchers typically assume for those factors, and the inter-connection among them. Three main branches of CDS valuation are reduced form model, structural form model and CAPM framework. In addition, corporate and sovereign CDS contracts have different risk profiles, for example, liquidity spreads with different maturity vary significantly for a corporate CDS but less so for a sovereign CDS because, in contrast with the corporate markets where a majority of the trading volume is concentrated on the 5-year CDS, the sovereign market has a more uniform trading volume across maturities.

Regarding to the difference, Part B investigates the relationship between the changes in corporate CDS spreads and the determinants implied by structural models of default, including firm leverage, volatility, risk-free interest rate and liquidity. I construct a liquidity measure for CDS contracts and find these determinants, especially the liquidity determinant, are significant and time-varying, by a dummy-variable regression and a Markov regime switching model.

Part C develops and tests a model to value sovereign CDS spreads with observable macroeconomic variables and a latent variable under a multifactor affine framework, imposing no-arbitrage assumptions and allowing macro variables to affect the dynamics of the full term structure of sovereign credit risk. This reduced form model successfully replicates the spreads level and outperforms modelling with only a latent variable. Incorporating macro factors improves the out-of-sample performance, especially in normal periods. Studying the sovereign CDS spreads of 22 countries, I find that two country-specific macro factors, inflation and real output, extracted via a Kalman filter, have long-lasting impacts and are able to explain a significant portion of the variation of spreads, while US financial variables explain a portion of the latent factor that cannot be captured by the macro factors. This spillover effect on sovereign markets from the United States" economy is stronger during stress periods.

The implications of this thesis are following. First, for quantitative analysts on CDS derivative pricing, a key concern is the number of factors sufficient for CDS valuation. The results of this thesis suggest that besides factors for credit risk, one more factor to measure liquidity risk should be priced in a model, in order to estimate a fair CDS value; second, for risk analysts on CDS portfolio, a simple OLS regression may fail to capture the true portfolio risk, instead, a more advanced model such as a regime switching model should be applied for risk analysis including stress testing and scenario analysis, etc.; third, for traders on international markets, it is essential to take into account the impacts of other countries, a strong spillover from other countries may easily ruin their profits if they focus only on local macroeconomic and financial variables.

However, there are several limitations of this thesis. First, I did not examine the performance of models under CAPM framework for CDS valuation, which is developing quickly and may help to solve the default spread puzzle: a larger-than-expected short-term default spread. Second, the data sample is only from 2004 to 2010. Those countries with big influences on credit market such as Portugal, Spain and U.S. are excluded due to data limitation. Adding those countries and extending data sample to 2012 may help us find more interesting stories and make the models more convincing. Third, I did not consider a more sophisticated model for sovereign CDS spreads, which may fail to reflect the reality well. For example, I assume a constant volatility through-out the sample period. However, the sovereign spreads are clearly much more volatile after 2007. A more technically appealing way is to allow for the potential of regime-switching or stochastic volatility in an affine credit model, or to allow for the impacts of trading behaviour on CDS spreads.

To overcome the above mentioned limitations, my future research work will compare the performance of reduced form models, structural form models and models under CAPM framework with a longer data sample size and a more flexible valuation model by including an exogenous financial market volatility analogous to Wu and Zhang (2008), or replacing a constant volatility with a stochastic volatility following Jacobs and Li (2008).

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