Structural Model of Credit Default Swap Spreads with the Equity Volatility and Jump Risk of Firms: An Empirical Analysis

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Abstract

This paper uses the equity volatilities and jump measures based on high-frequency stock price data to capture the movement of CDS spread. By using long-term (1-year Historical volatility) and short-term (1-year Realized variance) equity volatility as independent variables, we can explain the one-third of CDS spreads movement. Moreover, jump measures solely detect 12% of CDS spreads. As decompose the one-year realized variance (RV) to continuous realized variance (RV(C)) and jump measure, explanatory power increases 6% (adj. R^2 of 40%). In contrast, albeit combining the rating information, macro financial, and balance sheet variables with existing model, the increment of explanatory power is negligible (adj. R^2 of 41%).

I. Introduction

CREDIT DEFAULT SWAPS (CDS) TYPICALLY DESCRIBES a financial swap agreement between protection sellers and protection buyers regarding credit events. A protection buyer regularly pays premium to a protection seller for protection and the protection seller compensates the loss of reference bond when loss occurs by credit events.

In the past several years, credit derivatives are actively traded. According to BIS quarterly review, the market size of the credit default swaps (CDS) started from \$6.4 trillion in 2004, peaks at \$58.2 trillion in 2007, and decreased to \$25.1 trillion in 2012. Longstaff, Mithal, and Neis (2005) argue that by their nature, these innovative contracts provide researchers with a near-ideal way of directly measuring the size of the default component in corporate spreads. This paper suggests that CDS spreads capture more pure default risk compared to corporate bond spreads. CDS trading does not directly trade the reference bond itself and CDS buyers are protected by only credit events (Blanco, Bennan, March (2005)). On the other hands, corporate bonds include plenty of non-default components. For instance, corporate bond trades physical bonds, thus

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bond price reflects bond-specific illiquidity such as bid-ask spread (Alexander, Edwards, and Ferri (1998)). Furthermore, while calculating bond spreads, corporate bond and Treasury bond used different tax rate (Elton, Gruber, Agrawal, and Mann (2001)). In this sense CDS spread regards improved variable to measure the default risk.

However, after the financial crisis in 2008, CDS market size dramatically decreased. This trend represents that CDS spreads mislead investors to measure the corporate credit risk. Moreover, Kim, Choi and Hyung (2012) argue that CDS spreads reflect counterparty risk in its value, thus CDS spreads also reflect non-default components. Nevertheless, after Basel III regulation, CDS is obligatorily trading in Central Counterparty (CCP).[2] Thus, the CDS will more directly measure the default risk of the individual firms by eliminating counterparty risk. In this reason, CDS becomes improved measure of credit default.

This paper is organized as follows. Section I for introduction. Section II follows literature review and section III explains concrete methodology of using high-frequency data based on stochastic jump-diffusion model. Section IV describes the CDS spreads and explanatory variables. Section V presents result of the regression and comparison with result of Zhang et al. (2009). Section VI concludes and argues about improvement of the paper.

II. Related Research

The structural model of default is created by intuition of Black and Scholes (1973), contingent claim analysis (CCA). This model introduced by Merton (1974), and additionally researched by Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001), and Collin-Dufresne, Goldstein, and Martin (2001). Basic concept of structural model is firm counters the default when firm value decreases below outstanding debt value.

However, the past studies indicate that the structural model does not properly explain the credit risk. Contingent Claim Analysis (CCA) model fails to improve a naïve (riskless) model (Jones, Mason, and Rosenfeld 1984). Credit risk is explained not by one of credit measure factors - expected default, but by non-credit measure - state taxes (Elton, Gruber, Agrawal, and Mann (2001)). Huang and Huang (2003) compare several structure models and conclude that credit risk accounts for only a small fraction of the observed corporate Treasury yield spread. The structural models prone to generate extremely low spreads on the bonds that the models consider safe (usually low leverage and low asset volatility) and to generate very high spreads on the bonds considered to be very risky (Eom, Helwege, and Huang (2004)).

Longstaff, Mithal, and Neis (2005) suggest using CDS data instead of corporate to obtain measures of the default in corporate spreads to overcome this problem. As mentioned in the introduction, compared to corporate bonds, CDS more purely capture the default risk. Moreover, further investigate followed by Blanco, Brennan, and March (2005), Zhu (2006), and Zhang, Zhou and Zhu (2009).

[2] If CDS is trade without CCP, the requirements of capital are stricter then CDS within CCP. Thus, most of CDS will trade in CCP.

To see the dynamic movement of CDS spread, the other novel approach is connecting CDS movement with high-frequency stock price data. Andersen, Bollersleve, Diebold, and Labys (2001) mentioned using high-frequency intraday equity returns strengthened the theoretical basis for measuring and analysing realized volatilities. The stochastic measures from high-frequency data provide a high explanatory power than those from low-frequency data (Barnodrff-Nielsen and Shephard (2002), and Meddahi (2002)).

Zhang, Zhou, and Zhu (2009) combine these two approaches and attempts to explain the movement of CDS spreads, using the equity volatility and jump risk of individual firms by calculating from high frequency stock price data.

Our paper focuses on the specific time period – financial crisis (from September 2007 to August 2010). This paper finds the explanation power of the each component in the dramatic period of CDS movement (right before and after the financial crisis) by using high-frequency equity data. Zhang, Zhou, and Zhu (2009) investigate the determination of CDS spreads at the firm level, using realized variance, jumps, ratings, macro, and firm financial ratio from January 2001 to December 2003. Furthermore, CDS is sensitive to short term volatility and stock market volatility, which affects CDS premium (Norden and Weber (2009)). Thus jumps and volatility of the stock market would be important information to see the CDS premium.

With similar approach as Zhang et al. (2009), this paper focuses on different period when the CDS dynamically changed due to financial crisis. (September 2007 to August 2010). By focusing on different period, this paper provides varying result as time changed, furthermore compares the validity of the results, and figures out the reasons leaded to different results.

III. Basic Development and Ideas on High-Frequency Data

In this paper, I used high-frequency stock returns (five-minute frequency) to build up realized variance (RV), bipower variation (BV), and jump risk measures. The five-minute frequency is generally used since more frequent observations increase market microstructure noise (Ait-Sahalia, Mykland and Zhang (2005), Hanseen and Lunde (2006), and Zhang, Zhou and Zhou (2009)). Thus five-minute frequency stock price data is motivated by this bias-variance trade-off (Andersen, Bollersleve, and Diebold (2007)). This research assumes that the jumps in financial markets are rare and large. By this assumption, I explicitly estimate the jump intensity, jump variance, and jump mean.

Let $s_t \equiv logS_t$ denote the continuous logarithmic stock price as a jump diffusion stochastic model,

$$\boldsymbol{dS_t = \mu_t^s dt + \sigma_t^s dW_t + J_t^s dq_t}\,, \tag{1}$$

where μ_t^s and σ_t^s are, respectively, the drift and instantaneous volatility, W_t is a standardized Brownian motion, dq_t is a Poisson process with intensity λ^s,and J_t^s is a pure jump Levy process with increments. I adopted this notation from Zhang at el. (2009). If time is measured in daily units, the daily return, r_t, is measured in following way, $r_t \equiv s_t - s_{t-1}$. Likewise, intraday returns are calculated as follows,

$$r^s_{t,k} = s_{t,k\cdot\Delta} - s_{t,(k-1)\cdot\Delta} \ , \quad \textbf{(2)}$$

where $r^s_{t,k}$ refers to the k-th within-day return on day t and Δ is the sampling frequency (five-minute).

Barndorff-Nielsen and Shephard (2004, 2006) study suggests two general measures of Realized Variance and bipower variation in intraday.

$$RV_t \equiv \sum_{k=1}^{1/\Delta} (r^s_{t,k})^2 \ , \quad \textbf{(3)}$$

$$BV_t \equiv \frac{\pi}{2} \sum_{k=1}^{1/\Delta} |r^s_{t,k}| \cdot |r^s_{t,k-1}| \ . \quad \textbf{(4)}$$

As noted in Andersen, Bollerselve, and Diebold (2002), the Realized Variance satisfies

$$\lim_{m\to\infty} RV_t = \int_{t-1}^{t} \sigma_s^2 ds + \sum_{i=1}^{1/\Delta} (J^s_{t,i})^2 \ , \quad \textbf{(5)}$$

where $1/\Delta$ is the number of jumps within day t and $J^s_{t,i}$ is the jump size. Therefore, RV is a consistent estimator of integrated variance and the jump contribution.

For bipower variation, Barndorff-Nielsen and Shephard (2004, 2006) shows that integrated variance can be consistently estimated by the bipower variation under reasonable condition.

$$\lim_{m\to\infty} BV_t = \int_{t-1}^{t} \sigma_s^2 ds \ . \quad \textbf{(6)}$$

Thus, by subtract realized variance and bipower variation, $RV_t - BV_t$, we can discover a consistent estimator of the jump contribution. Moreover, Barndorff-Nielsen and Shephard (2004, 2006) suggest that using difference of variance and bipower variation; we can form the basis of a test for jumps by calculating relative jump measure (RJ).

$$RJ_t \equiv \frac{RV_t - BV_t}{RV_t} \ . \quad \textbf{(7)}$$

I adopted ratio test statistics of significant jumps on the basis of ratio statistics as defined in Equation (7):

$$z = \frac{RJ_t}{[(\left(\frac{\pi}{2}\right)^2 + \pi - 5) \cdot \Delta \cdot \max(1, \frac{TP_t}{BV_t^2})]^{1/2}} \ , \quad \textbf{(8)}$$

where tripower variation, TP_t, as follows:

$$\boldsymbol{TP_t} \equiv \frac{\mathbf{1}}{\mathbf{4}\Delta[\Gamma(\frac{\mathbf{7}}{\mathbf{6}}) \cdot \Gamma\left(\frac{\mathbf{1}}{\mathbf{2}}\right)^{-\mathbf{1}}]^{\mathbf{3}}} \cdot \sum_{k=3}^{1/\Delta} |\boldsymbol{r_{t,k}}|^{4/3} \cdot |\boldsymbol{r_{t,k-1}}|^{4/3} \cdot |\boldsymbol{r_{t,k-2}}|^{4/3} \quad . \qquad \textbf{(9)}$$

Following early drafts of the work reported, central limit theory for the linear jump statistic is used. As $\Delta \rightarrow 0, TP_t \xrightarrow{p} \int_{t-1}^{t} \sigma_s^4 ds$ and $z \sim N(0,1)$. The ratio test proves the existence of "significant jump" in a day and the size of the contribution to realized variance.

In implementation, I followed suggestion of Huang and Tauchen (2005) that theoretical Monte Carlo analysis indicates that microstructure noise biases the tests against detecting jumps, and that a simple lagging strategy corrects the bias. Thus, the equation is reformed as follows (j=1):

$$\boldsymbol{BV_t} \equiv \frac{\boldsymbol{\pi}}{\mathbf{2}} \sum_{k=2+j}^{\frac{1}{\Delta}} |\boldsymbol{r_{t,k}^s}| \cdot |\boldsymbol{r_{t,k-(1+j)}^s}| \ , \qquad \textbf{(10)}$$

$$\boldsymbol{TP_t} \equiv \frac{\mathbf{1}}{\mathbf{4}\Delta[\Gamma(\frac{\mathbf{7}}{\mathbf{6}}) \cdot \Gamma\left(\frac{\mathbf{1}}{\mathbf{2}}\right)^{-\mathbf{1}}]^{\mathbf{3}}} \cdot \sum_{k=2(1+j)}^{1/\Delta} |\boldsymbol{r_{t,k}}|^{4/3} \cdot |\boldsymbol{r_{t,k-(1+j)}}|^{4/3} \cdot |\boldsymbol{r_{t,k-2(1+j)}}|^{4/3} \quad . \qquad \textbf{(11)}$$

To measure the size of the jumps, I follow the assumption of Zhang et al. (2009) that there is at most one jump per day and jump size dominates returns on jump days. Andersen, Bollerslev, and Diebold (2007) suggest the way to measure the daily realized jumps ("significant jumps") as follows:

$$J_t^s = sign(\boldsymbol{r_t^s}) \times \sqrt{\boldsymbol{RV_t} - \boldsymbol{BV_t}} \times \boldsymbol{I}(\boldsymbol{z} > \Phi_{\alpha}^{-1}), \qquad \textbf{(12)}$$

where I(·) is indicator function, Φ is the probability of a standard normal distribution and α is the level of significance chosen as 0.999. For choosing the significance level, there are no conclusive criteria (Barndorff-Nielsen and Shephard (2004), Andersen, Bollerslev, and Diebld (2007), Huang and Tauchen (2005), Tauchen and Zhou (2008)). Thus, I choose strict significance level, α=0.999. By the ratio test with certain level of significance, we can detect the "significant jumps" and estimate the jump intensity (JI), jump mean (JM), and jump volatility (JV):

$$\mathrm{JI} = \frac{Number\ of\ jump\ days}{Number\ of\ trading\ days} \quad , \qquad \textbf{(13)}$$

$$\mathrm{JM} = \text{Mean of } \boldsymbol{J_t^s} \qquad \textbf{(14)}$$

$$\text{JV} = \text{Standard deviation of } \boldsymbol{J_t^s} \quad \textbf{(15)}$$

IV. Data Description

The data is collected from September 3, 2007 to August 31, 2010. Specific data collection is described as follows.

1. Credit Default Swap Spread (CDS Spread): CDS spread data are collected by data stream in weekly frequency.[3] CDS spread is used in last quotation in every week including all five-year CDS contract in senior grades written on U.S. entities (excluding sovereign entities) and denominated in U.S. dollars. After matching the account information and credit rating data, the 226 entities are selected.
2. Equity Price: (1) Based on CRSP daily data, average historical returns, historical volatility (HV), historical skewness (HS), and historical Kurtosis (HK) calculate for each entity over a specific time horizon (one year). (2) On the other hands, high-frequency stock price data is collected based on Trade and Quote (TAQ). With this data, realized volatility (RV), bipower variation (BV), and jump distribution parameters are calculated for the one-year horizon. All the data are transformed to five-minute frequency log returns, which are generally known to be quite robust to market microstructure noise (Tauchen and Zhou (2008)). I eliminate the before/after-hour trading data due to liquidity concern.
3. Balance Sheet Data: Leverage Ratio (LEV), Return on Equity (ROE) and Dividend Pay-out Ratio (DIV) data are collected from Compustat. Following Collin-Dufresne, Goldstein and Martin (2001), I use linear interpolation for the balance sheet information since the data are updated quarterly.

$$\textbf{Leverage Ratio (LEV)} = \frac{\textbf{Current debt} + \textbf{Long} - \textbf{term debt}}{\textbf{Total Equti} \ + \textbf{Current debt} + \textbf{Long} - \textbf{term debt}} \quad \textbf{(16)}$$

$$\textbf{Return on equity (ROE)} = \frac{\textbf{Pretax income}}{\textbf{Total Equtiy}} \quad \textbf{(17)}$$

$$\textbf{Dividend payout ratio (DIV)} = \frac{\textbf{Dividend payout per share}}{\textbf{Equity price}} \quad \textbf{(18)}$$

4. Rating Data: Rating data of each entity collected from Compustat based on S&P domestic long-term debt.

[3] Zhang at el. (2009) argue that composite quotes are available on a daily basis, but they choose a weekly data frequency, mainly because two reasons. First reason is that CDS data suffer from the staleness problem at daily frequency. Second reason is that using daily data is likely to under-estate the effect of firms' balance sheets on CDS pricing because balance sheet information is available only on a quarterly basis.

5. Macro Data: S&P 500 daily returns, VIX implied volatility for the S&P 500 index, 3-month Treasury rates and Term spread (difference between long-term Treasury rate (10 year) and short-term (three-month) Treasury rate) are collected from Datastream.

A. Summary Statistics

The period of this paper is from September 2008 to August 2010. Total 227 of the U.S. firms are selected which have full data in CDS spreads, stock price, balance sheet, and credit rating data during certain period. The ratings of the firms are distributed in AAA (1.77%; 4 firms), AA (7.08%; 16), A (30.09%; 68), BBB (44.69%; 101), BB (14.16%; 32), B (2.21%; 5), and below B (0%, 0) based on the rating announcement August 31 in 2007. Table II shows the summary statistics of all regression variables. The statistics of each regression variables are reported by different rating group. The group is divided to make each group evenly distributed. The rating AAA-A group includes grade from AAA to A (38.94%; 88 firms), BBB group includes only grade BBB (44.69%; 101), and BB and below group (16.37%, 37).

First of all, the mean of 5-year CDS spreads A, BBB, and BB and below are 116.47, 155.65, and 415.24 basis point, respectively. Moreover, standard deviation of BB and below group is more than two times higher than that of other two groups (Table I. Panel A). This results show that CDS spreads increase as credit rating decreases and CDS spreads of lower credit rating group are more volatile. As mentioned at the introduction, CDS spreads directly reflect default risks. Thus, as credit rating is lower (which means the firm has higher probability of default), the CDS spreads is higher. In time-series manner, 5-year CDS spreads dramatically have increased after September 2008, during the crisis, and decreases one year after September 2009. Furthermore, magnitude of volatility is extraordinarily high for BB and below group (Figure 1. (a)).

Figure 1. (b) represents 1-year historical equity volatility of stock price of each group. Similar with movement of CDS spreads, historical volatility increases during the financial crisis and the magnitude of volatility is higher when the grade of credit is lower. High equity volatility can increase the probability of reaching default boundary, thus this result can explain the large CDS spreads in low quality credit group. Moreover, we can eminently perceive that historical volatility and realized volatility is correlated (Figure 1. (c)). However, realized volatility captures the movement of stock price in a more timely manner (Figure 1. (b) and (c)).

Regarding the jump measures, the jump occurs 3.54% for whole sample and high credit quality group (AAA-A) is slightly lower than other grades (BBB, 5.22%; BB and below, 4.51%). Mean of jump is positive for AAA-A group and negative for BBB and BB and below group, moreover. BB and below group have lowest value. This result roughly shows about the sign and magnitude of jumps that high credit quality group has more frequent positive sign or larger positive magnitude than low credit quality group (Figure 1. (d)). Frequent negative jumps can increase the default of probability of the firms which leads to increase CDS spreads.

Historical skewness of the each group has all negative value and junk bond group is slightly lower than others (AAA-A, -0.18; BBB, -0.27; BB and below, -0.35). Thus, as the credit quality decreases, negative tail is getting thicker (Table I. Panel A).

Concerning to balance sheet information, return-on-equity (ROE) is higher for high credit quality group (5.66%), lower for low quality group (0.85%). Superior ROE indicates the high efficiency of using capital which leads to low PD. On the other hand, leverage ratios (LEV) are exactly opposite, greater for low quality group (56.27%) and lesser for high quality group (42.18%). High LEV arises the dramatic outcomes which towards to strengthen default probability.

V. Empirical Evidence

Before explaining the outcomes, Table II briefly characterizes expected signs of CDS spreads by movement of each variable with economic intuition. Default is defined by Merton (1974) and contingent claim analysis (CCA). Probability of default (PD) increases when firm value is close to the value of outstanding debt.

1. Expected equity returns: The expected equity returns implies growth rate of firm value. High expected equity returns increase firm value. Therefore, firm value is located farther from value of outstanding debt which decreases the probability of default. *Decreases the CDS spreads.*
2. Equity volatility: Generally, volatility captures not only positive but also negative deviation. Thus, we cannot readily expect that high equity volatility increases the PD. However, high equity volatility firm has high probability to reach the boundary of default compared to low equity volatility firm. Within the contingent-claims analysis, structures of a short position in a put option are comparable to the debt claim. As option values increase with volatility, CDS spreads should increase with volatility. *Increases the CDS spreads.*
3. Equity skewness: Negative skewness indicates the equity returns are more distributed in negative side. Frequent negative returns decrease the firm value which leads to increase the PD. *Increase the CDS spreads.*
4. Equity Kurtosis: Positive kurtosis specifies fat-tailness of equity returns. Fat-tailness implies dynamic outcomes with vast volatility which arise the probability of reaching the boundary of outstanding debt. *Increase the CDS spreads.*
5. Equity Jump (Negative): Equity jumps are considerably correlated with equity volatility. Especially, negative-side jumps fall the firm value and increase PD. *Increase the CDS spreads.*
6. Leverage Ratio: Default is triggered when the leverage ratio reaches unity. Thus, leverage ratio increases the PD. Moreover, leverage ratio yields the outcome more dramatically. High leverage firms have more volatile returns than low leverage firms'. *Increase the CDS spreads.*

7. Dividend Pay-out Ratio: Dividend is pay-out from capital of the firm. Large pay-out compared to earnings will decrease the capital more severely, which leads to decrease firm value and increase PD. *Increase the CDS spreads.*
8. Return on Equity: Return on Equity captures the efficiency of producing earnings. High return on equity increases the firm value and decreases PD. *Decrease the CDS spreads.*
9. Expected Market Returns: Expected market returns reflect the overall business climates. Even if the condition remains constant for a firm, changes in market returns vary the PD of the overall firms. High expected market returns render firms to enlarge their firm value. *Decrease the CDS spreads.*
10. Market Volatility: Market volatility reflects industrial venerability. Similar with equity volatility, market volatility changes the volatility of the entire firms. *Increase the CDS spreads.*
11. Short-term Interest Rate: Within the stochastic model, spot rate is directly related with the risk-neutral drift of the firm value process. Thus, high spot rate increases the risk-neutral drift and let firm value locate farther from default boundary (Longstaff and Schwartz (1995)). Duffee (1998) supports this argument that a higher drift reduces the probability of default, and in turn, reduces the credit spreads. Nevertheless, Zhang, Zhou, and Zhu (2009) also mention spot rate reflects a tightened monetary policy and triggers the recession. *Ambiguous.*
12. Term Spread: Litterman and Scheinkman (1991) find that the two most important factors driving the term structure of interest rates are the level and slope of the term structure. If an increase in the slope of the Treasury curve increases the expected future short rate, then by the same argument as above, it should also lead to a decrease in CDS spreads. From a different perspective, a decrease in yield curve slope may imply a weakening economy. Zhang, Zhou, and Zhu (2009) support the argument that a steeper slope of the term structure is an indicator of improving economic activity in the future, but it can also forecast an economic environment with a rising inflation rate and a tightening of monetary policy. *Ambiguous.*

A. General Ordinary Least Square (OLS) Regression Model

Section A explains the movement of CDS spreads by using the OLS regression model. The model uses equity volatilities, jumps, macro financial data, and balance sheet information to capture the CDS spreads.

$$\begin{aligned} \boldsymbol{CDS_{i,t}} &= \boldsymbol{c + b_v Volatilities_{i,t-1} + b_j Jumps_{i,t-1} + b_r Ratings_{i,t-1}} \\ &\quad \boldsymbol{+ b_m Macro_{i,t-1} + b_f Firm_{i,t-1} + \varepsilon_{i,t},} \end{aligned} \tag{19}$$

where the explanatory variables are described in data description section.

The model in Section B uses only equity volatilities and equity jumps to examine the role. Section C extends regression model with balance sheet information and macro financial variables. Section D checks robustness of the model by using change measure of each variable.

B. Regression with Equity Volatilities and jumps

Section B implements the regression that measuring CDS spreads by using equity volatilities and jumps (Table III). The OLS regression model is follows:

$$CDS_{i,t} = c + b_v Volatilities_{i,t-1} + b_j Jumps_{i,t-1} + \varepsilon_{i,t}, \tag{20}$$

Independent variable of Regression (1) which is one-year historical volatilities of equity, explains 30% of CDS spreads. This result is lower than the result of Zhang, Zhou, and Zhu (2009; Table 3, regression 1, adjusted R^2 of 45%). Regression (2) uses one-year realized variance as an independent variable and yield an adjusted R^2 of 21%. Regression (3) combines historical volatilities and realized variance and described one-third of CDS spreads movement. The signs of the coefficients in regression (1), (2), and (3) express same sign that we expected in Table II and all significant. Thus, we can check that high volatility of equity increases the CDS spreads. Zhang, Zhou, and Zhu (2009) recommend that a combination of both long- and short-run volatilities can better reflect the time variation in equity volatility, since within the framework of Merton (1974), the equity volatility is time varying, although the asset-value volatility is constant.

On the other hand, Regression (4) uses historical skewness and kurtosis as explanatory variables. Although they combined these two variables, they explain almost negligible (adjusted R^2 of 0.0044%). In contrast to regression (4), regression (5) and (7) includes jump variables and captures around 10% of CDS spreads movement. Jump intensity (JI) has a most strong effect that 1 % increase of intensity increases 6.96-7.57 basis points of CDS spreads. Jump means (JM) decompose to positive jumps and negative jumps and regression (6) used these components to check CDS spreads, still, explanatory power of these two variables is limited (adjusted R^2 of 0.23%). Nonetheless, explanatory power of regression (7) increases by 3% compared to regression (5). This represent that by combining the positive and negative jumps with other jump measures, the explanatory power is slightly improved. The coefficient of each signed jump has asymmetric. The coefficient of the negative jumps is significant with correct sign that we expected. On the contrary, the positive jumps positive jump shows different sign with insignificant coefficient.

In regression (8), we decompose the realized volatility to continuous realized variance and jump measures. By decomposition, the explanatory power is 6% increases (adjusted R^2 of 40%).

C. Extended Regression with Rating, Balance Sheet and Macro Financial Variables

Section C extended the independent variables from regression model in Section B (Table IV). Specified extended variable is credit rating information, macro financial data (S&P 500, VIX, 3-month Treasury rate, Term spread (10Y-3M Treasury rate)), balance sheet information (return-on-equity (ROE), leverage ratio (LEV), and dividend pay-out ratio (DIV)). The OLS regression model is follows:

$$CDS_{i,t} = c + b_v Volatilities_{i,t-1} + b_j Jumps_{i,t-1} + b_r Ratings_{i,t-1} + b_m Macro_{i,t-1} + b_f Firm_{i,t-1} + \varepsilon_{i,t}, \tag{21}$$

In regression (1), this paper categorized the rating groups into 3, AAA-A, BBB, and Below BB.[4] By comparing the dummy variables between different rating groups, we can easily understand the high credit rating group is significantly lower than low credit rating group.[5] Yet, compared to Zhang, Zhou and Zhu (2009), the main difference of result of regression is explanatory power of credit rating information. Regression (1), using credit ratings alone, yields an adjusted R^2 of 11%, a level lower than the main result of Zhang, Zhou, and Zhu (2009; see Table 3, regression 1, adjusted R^2 of 45%). There exist two possibilities to explain the considerable difference of degree of explanation. One of the reasons is different selection criterion. Zhang, Zhou and Zhu (2009) used seven different dummies depended on credit ratings. However, this paper uses 3 categorized groups to make each group represent itself by evenly distributing them. The other reason is credit rating data selection by criteria. The credit rating data is selected based on September 2007 and assumed that credit rating is constant during the regression period. Yet, during the middle of 2008, the financial crisis hit U.S. market and credit ratings have dramatically changed. Thus, credit rating based on the September 2007 is not adequate representative group. In other words, the credit ratings in 2007 would reflect the risk inadequately. In this sense, regression (3) combines the volatility and jump measure with credit rating, which leads to 1% increment of adjusted R^2 from regression (2).

Regression (4) presents that combination of rating, macro, and balance sheet variables. This regression explains addition 1% from regression (1). Thus macro financial variables and balance sheet information provide limited contribution for explaining CDS spreads. All the expected signs of macro financial variables and balance sheet information are delivered in Table II. Signs of the S&P 500 returns, ROE, and LEV are opposite, but this coefficient is insignificant and the portion of explanatory power of CDS movement is limited. Thus the relationships between these variables and CDS spreads are inconclusive. Instead, short rate has significantly negative sign with considerable coefficient. 1% of short rate increase will falls 31.23-47.43 basis point of credit spread. This argument is consistent with Longstaff and Schwartz (1995) that within structure model, a higher short rate increases the risk-neutral drift of the firm-value process and reduces PD (Table II).

Regression (5) implements all of the independent variables and explains additional 1% from the regression (2). This conclusion is similar with the regression (4). Interestingly, signs of term spread are significantly opposite in regression (4) and (5). This reflects the ambiguous of the term spread to CDS spreads (Table II).

These results of regression imply that the credit rating explains 11% of the CDS movement, furthermore, macro financial variables and balance sheet information are more negligible. On the other hands, equity volatilities and jumps captures 40% of the CDS movement.

[4] As mentioned in data description chapter, group selection criterion is evenly distributed sample size in each group.
[5] Due to mechanism of regression with dummy variables, Rating (AAA to A) group is standard and coefficient of Rating (BBB) and Rating (Below BB) is relative coefficient from AAA. Thus, coefficient of Rating (AAA to A) is lower than Rating (BBB) and Rating (Below BB).

D. Robustness Check

Section D checks the robustness of the regression in section B and C. Collin-Dufresne, Goldstein, and Martin (2001) recommends the regression analysis which can examine the robustness of the regression. (Table V). The OLS regression model is follows:

$$\Delta \boldsymbol{CDS}_{i,t} = \boldsymbol{c} + \boldsymbol{b}_v \Delta \boldsymbol{Volatilities}_{i,t-1} + \boldsymbol{b}_j \boldsymbol{Jumps}_{i,t-1} + +\boldsymbol{b}_m \Delta \boldsymbol{Macro}_{i,t-1} + \boldsymbol{b}_f \Delta \boldsymbol{Firm}_{i,t-1} + \boldsymbol{\varepsilon}_{i,t}, \tag{22}$$

The idea of this regression is that using same variables with different measure and compares the result with original one. Similar to the Collin-Dufresne, Goldstein, and Martin (2001) and Zhang, Zhou, and Zhu (2009), the explanatory power is considerably lower than original's. However, change of 1-year historical volatility and 1-week continuous realized variance is significant in regression (2) and (3). Therefore, long-term and short-term volatilities are crucial factors for explaining changes in CDS spreads.

VI. Conclusion

I have investigated the effect of numerous factors on Credit Default Swap spreads based on the economic intuitions (Table II). This paper reflects the equity volatility and jump risk of firms and examines the determinant by empirical analysis.

Starting from the structural model, we calculated equity volatilities in two terms, long-term historical volatilities (1-year interval) and short-term historical volatilities based on high-frequency stock price data. By using long-term and short-term equity volatility as independent variables, we can explain the one-third of CDS spreads movement Moreover, by re-implementing robust check regression, 1-year historical volatility and 1-week continuous realized variance measure remain robust.

By high-frequency data we can also detect the jump measures (JI, JV, JM PJ, and NJ). These jump measures themselves solely detect 12% of overall variation. As jump measures combine with volatility measures, the explanatory power increases 6% (adj. R^2 of 40%).

On the contrary, combining the rating information, macro financial, and balance sheet variables with existing model, the increment of explanatory power is negligible (adj. R^2 of 41%).

This paper provides several different results compared to Cossin and Hricko (2002) and Zhang, Zhou, and Zhu (2009). Cossin and Hricko (2002) argue that the rating is the most important single source of information on credit risk. Still, most significant difference is low explanatory power of credit rating information. In this paper, credit rating explains only 11% of the total variation (compared to 47% in Zhang, Zhou, and Zhu (2009)). The one of the reasons can be expected by grouping criteria and the other is failure of capturing of credit default risk.

Further research will be needed to investigate the influence of determinant with recent time interval (after 2010) and find out the time-varying of importance of determinants.

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<Appendix>

Table I. Summary Statistics

Panel A: Firm-specific variables

Variables	AAA-A Mean	AAA-A Std. Dev	BBB Mean	BBB Std. Dev	BB and below Mean	BB and below Std. Dev	Whole sample Mean	Whole sample Std. Dev
CDS (basis point)	116.47	239.27	155.65	172.00	415.24	556.57	183.92	313.50
1-week return (%)	-9.81	221.43	-9.95	218.95	-15.22	329.85	-10.78	235.48
1-year HV (%)	1.86	0.80	1.77	0.74	2.57	1.07	1.91	0.81
1-year HS	-0.18	0.22	-0.27	0.25	-0.35	0.17	-0.28	0.23
1-year HK	1.78	1.33	1.75	1.69	1.16	0.95	1.62	1.36
1-week RV (%)	2.89	1.85	2.80	1.77	4.06	2.28	2.97	1.85
1-week RV(C) (%)	2.87	1.83	2.79	1.78	4.06	2.29	2.96	1.86
1-week RV(J) (%)	0.05	0.41	0.04	0.22	0.02	0.17	0.02	0.12
1-year JI (%)	3.41	0.70	5.22	1.08	4.51	1.04	3.44	0.73
1-year JM(%)	0.73	0.63	-0.11	0.22	-0.62	0.70	-0.31	0.79
1-year JV (%)	4.89	1.16	3.95	0.18	4.72	0.22	3.54	0.25
ROE (%)	5.66	7.81	4.50	3.00	0.85	13.30	4.36	4.76
LEV (%)	42.18	2.28	46.53	1.19	56.27	4.44	46.43	2.05
DIV (%)	36.13	5.12	39.55	16.45	18.15	64.23	34.71	14.66

Panel B: Macro financial variables

	Mean	Std. dev
S&P 500 return (%)	-0.21	3.76
S&P 500 implied vol (VIX, %)	29.50	9.28
3-month Treasury rate (%)	0.93	1.19
Term spread: 10Y - 3M (%)	2.62	0.92

The Table I represents the summary statistics of the regression variables. Panel A is the summary statistics of the different credit rating groups (AAA-A, BBB, and BB and below) based on 226 firms. Selection criteria are based on the data accessibility of full data of 5-year CDS spreads, stock prices, credit rating and balance sheet information in U.S. market. Panel B is the summary statistics of macro financial variables. The whole sample period is covered from September 2007 to August 2010.

Table II. Theoretical Sign Prediction toward CDS Spreads

Variables	Predicted Sign	Economic Intuition
Expected equity returns	-	Positive equity returns reduce the probability of default (PD)
Equity volatility	+	High equity volatility increases the probability of reaching default boundary.
Equity Skewness	-	Positive skewness data are more distributed in positive side. Thus, High positive skewness occurs negative effect to CDS spread.
Equity Kurtosis	+	High kurtosis means equity returns are fat-tailed. Thus, it will increase the probability of extreme returns.
Equity Jump (Negative)	+	Jumps show the extreme movement of equity. Especially negative side jumps increase the PD. (Zhou (2001))
Leverage Ratio	+	High leverage firms have more volatile outcomes compared to low leverage firms. (Merton (1974))
Dividend Payout Ratio	+	High dividend payment will reduce capital of the firms, thus increase the PD.
Return on Equtiy	-	High ROE shows high efficiency of increasing capital which leads to decreasing PD.
Expected Market return	-	High expected market return reflects positive industrial environment.
Maket Volatility	+	High volatility shows venerability of industrial environment.
Short-term Interest Rate	Ambiguous	Since a higher spot rate increases the risk-neutral drift of the frim value process and lowers PD (Longstaff and Schwartz (1995) and Duffee (1998)). Nonetheless, it may reflect a tightened monetary policy stance and therefore PD increases. (Zhang, Zhou, and Zhou (2009))
Term spread	Ambiguous	Zhang, Zhou, and Zhu (2009) discusses that a steeper slope of the term structure is an indicator of improving economic activity in the future, but it can also forecast an economic environment with a rising inflation rate and a tightening of monetary policy.

Table III. Regression with Equity Volatilities and Jumps

	Dependent variable: Five-year CDS spread (basis point)							
Independent Variables	1	2	3	4	5	6	7	8
Constant	98.70	131.89	43.47	223.94	22.31	212.06	9.17	-57.25
	(7.59)	(12.24)	(3.79)	(12.15)	(1.31)	(11.31)	(0.51)	(-4.27)
1-year HV	35.18		27.75					20.23
	(27.38)		(22.42)					(15.14)
1-year HS				-28.16				
				(-18.99)				
1-year HK				-1.67				
				(-14.28)				
1-year RV		14.61	13.72					
		(50.52)	(47.49)					
1-year RV(C)								11.91
								(62.22)
1-year JI (%)					7.57		6.96	3.25
					(13.64)		(12.61)	(6.41)
1-year JM(%)					-2.24			
					(-6.18)			
1-year JV (%)					1.81		2.29	9.90
					(12.47)		(19.06)	(0.79)
1-year JP (%)						5.46	1.33	20.13
						(1.49)	(0.36)	(5.97)
1-year JN (%)						16.55	11.98	19.63
						(4.39)	(3.2)	(5.67)
Adj. R^2	0.30	0.2053	0.344	0.00	0.09	0.00	0.12	0.40
Obs.	23779	23779	23779	23779	23779	23779	23779	23779

The Table III represents the regression with equity volatilities and jumps. The data is collected from September 2007 to August 2009 based on 226 U.S. firms. The OLS regression is described as follows:

$$\boldsymbol{CDS_{i,t} = c + b_v Volatilities_{i,t-1} + b_j Jumps_{i,t-1} + \varepsilon_{i,t}}$$

Independent variables present one-year historical volatility (HV), historical skewness (HS), historical kurtosis (HK), realized variance (RV), continuous realized variance (RV(C)), jump intensity(JI), jump mean (JM), jump volatility (JV), positive jump (JP), and negative jump (JN).

Table IV. Extended Regression

Independent Variables	Dependent variable: Five-year CDS spread (basis point)									
	1		2		3		4		5	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant			-54.80	-4.1						
1-week return			1.17	6.85	1.18	6.88			0.93	5.24
1-year HV			19.01	14.11	18.52	13.76			19.02	14.12
1-week RV©			12.16	62.44	12.14	62.37			12.17	61.77
1-year JI			3.22	6.37	3.11	6.15			3.36	6.65
1-year JV (%)			7.96	0.64	7.53	0.6			12.52	1.00
1-year JP (%)			1.72	5.07	17.23	5.08			16.89	5.00
1-year JN (%)			2.25	6.46	22.58	6.49			22.70	6.55
Rating (AAA to A)	142.39	5.21			-104.31	1.33	52.82	1.61	-20.42	-0.84
Rating (BBB)	40.89	1.09			29.34	8.28	40.57	1.08	28.50	1.28
Rating (Below BB)	346.67	6.91			246.09	-5.81	346.12	6.84	243.6	8.13
S&P 500 return							0.62	1.74	1.58	4.67
S&P 500 implied vol (VIX)							2.02	11.2	0.58	3.47
Short rate							-31.23	-5.52	-47.43	-9.16
Term spread							10.96	2.63	-30.76	-7.97
ROE							-0.01	-0.26	-0.01	-0.49
LEV							-0.08	-1.47	-0.07	-1.5
DIV							0.02	2.41	0.01	1.46
Adj. R^2	0.11		0.40		0.41		0.12		0.41	
Obs.	23779		23779		23779		23779		23779	

The Table IV describes the extended regressions with credit rating, macro financial, and balance sheet information. The data is collected from September 2007 to August 2009 based on 226 U.S. firms. The OLS regression is described as follows:

$$CDS_{i,t} = c + b_v Volatilities_{i,t-1} + b_j Jumps_{i,t-1} + b_r Ratings_{i,t-1} + b_m Macro_{i,t-1} + b_f Firm_{i,t-1} + \varepsilon_{i,t},$$

Independent variables contain volatility variables which explain at Table III, three different credit rating groups, returns of S&P 500, implied volatility of S&P 500 (VIX), three-month Treasury rate (Short rate), Term spread (difference between ten-year Treasury bond rate and three-month Treasury rate), return-on-equity (ROE), leverage ratio (LEV) and dividend pay-out ratio (DIV).

Table V. Regression with Change of Variables

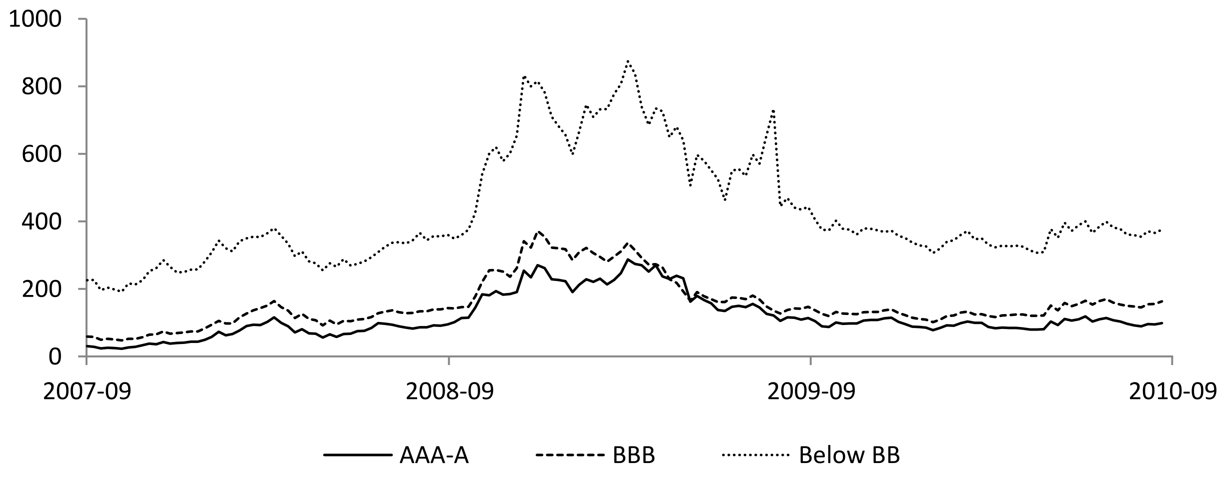
	Dependent variable: Five-year CDS spread (basis point)					
Independent Variables	1		2		3	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-0.22	-0.32	1.68	0.81	1.78	0.86
1-week return			-2.91	-35.70	-2.92	-34.66
Δ1-year HV			52.54	17.36	52.80	17.42
Δ 1-week RV(C)			0.37	2.65	0.38	2.68
1-year JI			-3.67	-0.32	-3.63	-0.31
1-year JV (%)			-5.76	-1.48	-5.84	-1.50
1-year JP (%)			4.41	2.73	4.40	2.72
1-year JN (%)			-0.90	-0.54	-0.88	-0.53
S&P 500 return	-1.17	-5.74			0.40	1.96
Δ S%P 500 implied vol (VIX)	0.53	2.11			0.24	0.98
Δ Short rate	-11.02	-2.59			-13.02	-3.16
Δ Term spread	-8.54	-2.15			-9.81	-2.55
Δ ROE	-0.04	-0.64			-0.08	-1.15
Δ LEV	-0.12	-1.04			-0.17	-1.55
Δ DIV	0.02	0.92				
Adj. R^2	0.0048		0.0678		0.0685	
Obs.	23778		23778		23778	

Table V demonstrates the extended regression with change of variables. The data is collected from September 2007 to August 2009 based on 226 U.S. firms. The OLS regression is styled as follows:

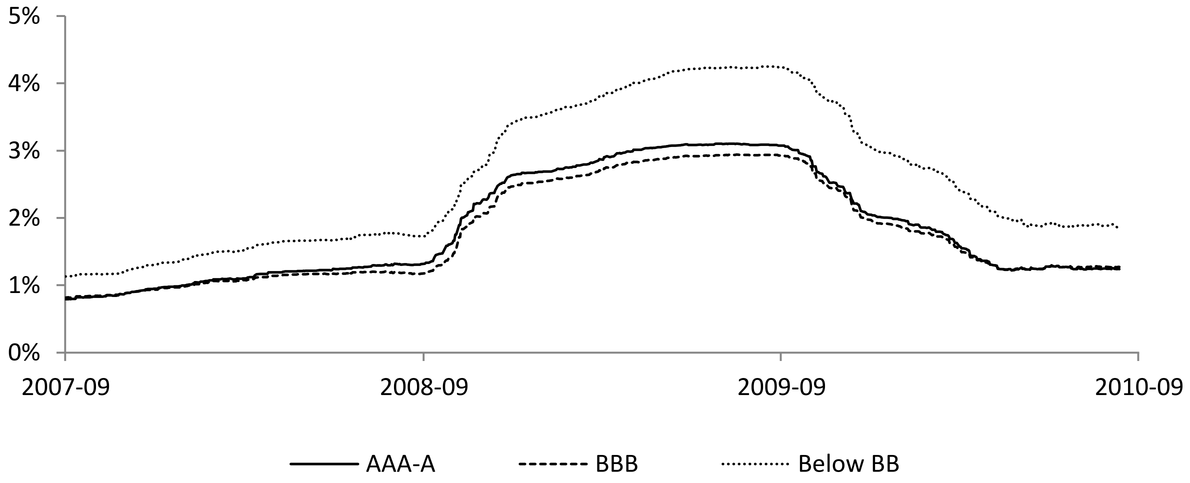
$$\Delta \boldsymbol{CDS_{i,t}} = \boldsymbol{c} + \boldsymbol{b_v}\Delta\boldsymbol{Volatilities_{i,t-1}} + \boldsymbol{b_j Jumps_{i,t-1}} + +\boldsymbol{b_m M}\Delta\boldsymbol{acro_{i,t-1}} + \boldsymbol{b_f}\Delta\boldsymbol{Firm_{i,t-1}} + \boldsymbol{\varepsilon_{i,t}},$$

Figure 1. 5-year CDS Spreads and Volatility Risks by Rating Groups

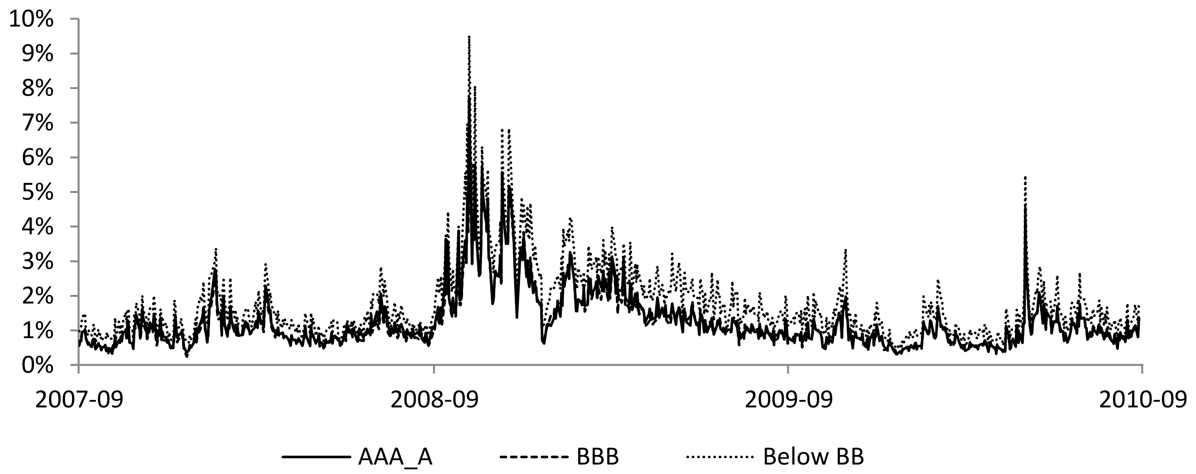
CDS spreads of each group are calculated as equally weighted portfolio. The solid line, dotted line, and grey line represent AAA-A, BBB, and Below BB, respectively.



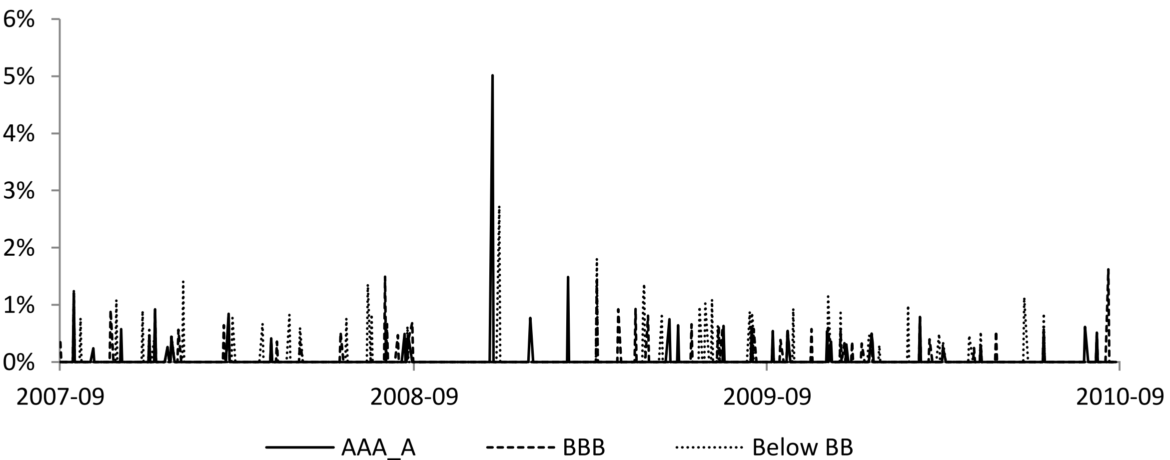
(a) 5-year CDS Spreads (basis point)



(b) 1-year Historical Volatility: HV (%)



(c) 1-week Realized Volatility: RV(C) (%)



(d) 1-week jump volatility: RV(J) (%)