Explaining Credit Default Swap Spreads with Equity Volatility and Jump Risks of Individual Firms*

Benjamin Yibin Zhang†
Hao Zhou‡
Haibin Zhu§

First Draft: December 2004
This Version: May 2005

Abstract

This paper explores the effects of firm-level volatility and jump risks on credit spreads in the credit default swap (CDS) market. We use a novel approach to identify the realized jumps of individual equity from high frequency data. Our empirical results suggest that the volatility risk alone predicts 50% of CDS spread variation, while the jump risk alone forecasts 23%. After controlling for ratings, macro-financial variables, and firms' balance sheet information, we can explain 75% of the total variation. These findings are in sharp contrast with the typical lower predictability and/or insignificant jump effect in the credit risk market. Moreover, firm-level volatility and jump risks show important nonlinear effect and strongly interact with the firm balance sheet information, which is consistent with the structural model implications and helps to explain the so-called credit premium puzzle.

JEL Classification Numbers: G12, G13, C14.
Keywords: Credit Default Swap; Credit Risk Pricing; Credit Premium Puzzle; Realized Volatility; Realized Jumps; High Frequency Data.

*The views presented here are solely those of the authors and do not necessarily represent those of Moody's KMV, Federal Reserve Board, and the Bank for International Settlement. We thank Tim Bollerslev, Greg Duffee, Jingzhi Huang, Matt Pritsker, George Tauchen, and Min Wei for detailed discussions. Commments from seminar participants at Federal Reserve Board and 2005 FDIC Derivative Conference are greatly appreciated.

†Moody's KMV, New York. E-mail: ben.zhang@mkmv.com. Tel.: 1-212-553-4543.

‡Federal Reserve Board, Washington DC. E-mail: hao.zhou@frb.gov. Tel.: 1-202-452-3360.

§Bank for International Settlements, Basel-4002, Switzerland. E-mail: haibin.zhu@bis.org. Tel.: 41-61-280-9164.

Explaining Credit Default Swap Spreads with Equity Volatility and Jump Risks of Individual Firms

Abstract

This paper explores the effects of firm-level volatility and jump risks on credit spreads in the credit default swap (CDS) market. We use a novel approach to identify the realized jumps of individual equity from high frequency data. Our empirical results suggest that the volatility risk alone predicts 50% of CDS spread variation, while the jump risk alone forecasts 23%. After controlling for ratings, macro-financial variables, and firms' balance sheet information, we can explain 75% of the total variation. These findings are in sharp contrast with the typical lower predictability and/or insignificant jump effect in the credit risk market. Moreover, firm-level volatility and jump risks show important nonlinear effect and strongly interact with the firm balance sheet information, which is consistent with the structural model implications and helps to explain the so-called credit premium puzzle.

JEL Classification: G12, G13, C14.

Keywords: Credit Default Swap; Credit Risk Pricing; Credit Premium Puzzle; Realized Volatility; Realized Jumps; High Frequency Data.

1 Introduction

Structural-form approach on the pricing of credit risk can provide important economic intuitions on what fundamental variables may help to explain the credit default spread. The seminal work of Merton (1974) points to the importance of leverage ratio, asset volatility, and risk-free rate in explaining the cross-section of default risk premia. Subsequent extensions in literature include the stochastic interest rate process proposed by Longstaff and Schwartz (1995); endogenously determined default boundaries by Leland (1994) and Leland and Toft (1996); strategic defaults by Anderson et al. (1996) and Mella-Barral and Perraudin (1997); and the mean-reverting leverage ratio process by Collin-Dufresne and Goldstein (2001). These generalizations call for time-varing macro-financial variables and firm-specific accounting informations as key determinants of the credit risk spreads. Further development of the jump–diffusion default model along the lines of Zhou (2001) indicates that jump intensity and volatility risks of firm value should have a strong impact on the credit spreads.

Despite their theoretical insights in understanding default risk, the empirical performance of structural-form models is far from satisfactory. There has been recently a burgeoning literature that documents the large discrepancy between the predictions of structural models and the observed credit spreads, which is also known as the credit premium puzzle (Amato and Remolona, 2003). For instance, Huang and Huang (2003) calibrate a wide range of structural models to be consistent with the data on historical default and loss experience. They show that in all models credit risk only explains a small fraction of the historically observed corporate-treasury yield spreads. In particular, for investment grade bonds, structural models typically explain only 20-30% of observed spreads. Similarly, Collin-Dufresne et al. (2001) suggest that default risk factors have rather limited explanatory power on variation in credit spreads, even after the liquidity consideration is taken into account. A recent study by Eom et al. (2004) finds that structural models do not always under-predict the credit spreads, rather, those models produce large pricing errors for corporate bonds. Moreover, incorporating jumps in theory should explain better the level of credit spreads even for investment-grade entities with short maturities (Zhou, 2001), however, empirically how to measure the jump risks and their impacts on the default premia is still an open question.

In this paper, we argue that the unsatisfactory performance of structural models may be in part attributed to the fact that the impacts of volatility and jump risks are not treated seriously. A prevalent practice is to use the average equity volatility within each rating category in calibration, which is subject to the "Jensen inequality" problem if the true impact of volatility on credit spreads is nonlinear. Even when firm-level equity volatility is used, historical volatility based on daily equity returns is often used, which tends to smooth out the short term impact of volatility on credit spreads, especially the jump risk impacts. More importantly, when jump effect is measured as historical skewness, it may over-detect a model with asymmetric distribution but no jumps while under-detect a model with symmetric jump distributions. The idea of emphasizing the link between equity volatility and jump risks on the one hand, and credit spreads on the other, is not new. Campbell and Taksler (2003) and Kassam (2003) observe that recent increases in corporate yields can be explained by the upward trend in idiosyncratic equity volatility. Collin-Dufresne et al. (2003) suggest that the jump risk alone does not explain a significant proportion of the observed credit spreads of aggregate portfolios. Instead, its impact on the contagion risk turns out to be associated with a much larger risk premium. Cremers et al. (2004a,b) measure volatility and jump risk from prices of equity index put options. They find that adding jumps and jump risk premia significantly improve the fit between predicted credit spreads and the observed ones.[1]

Our contribution is to use high frequency return data of individual firms to decompose the realized volatility into a continuous part and a jump part, following the theoretical work by Barndorff-Nielsen and Shephard (2003a). With stronger assumptions, we are able to filter out the realized jumps and isolate the impacts associated with jump intensity, jump volatility, and negative jumps. Therefore we can examine the credit spreads more thoroughly with short term volatility and various jump risk measures, in addition to the long-run historical volatility. Recent literature suggests that realized volatility measures from high frequency data provide a more accurate measure of the short term volatility (Andersen et al., 2001; Barndorff-Nielsen and Shephard, 2002b; Meddahi, 2002). Within the realized volatility framework, the continuous and jump contributions can be separated by comparing the difference between bi-power variation and quadratic variation (see, Barndorff-Nielsen and Shephard, 2004; Andersen et al., 2004; Huang and Tauchen, 2004, for the discussion of this methodology). Considering that jumps on financial markets are usually rare and of large sizes, we further assume that (1) there is at most one jump per day, and (2) jump size

[1] In this paper, we refrain from using option-implied volatility and jump risk measures, because they are already embedded with risk premia, which may have similar time-variation as credit spreads and need to be explained by the same underlying risk measures as well. We shall rely on historical or realized measures of volatility and jump risks.

dominates daily return when it occurs. With filtered daily jumps, we can estimate the jump intensity, jump mean (further decomposed into means of positive and negative jumps), and jump volatility. We apply these new volatility and jump risk measures to explain the credit default swap spreads.

Our empirical results suggest that long-run historical volatility, short-run realized volatility, and various jump risk measures all have statistically significant and economically meaningful impacts on the credit spreads. The realized jump measures explain 23% of total variations in credit spreads, while historical skewness and kurtosis measures for jump risk only explain 3%. It is worth noting that volatility and jump risks alone can predict 53% of the spreads variations. After controlling for ratings, macro-financial variables, and firms' accounting information, the signs and significances of jump and volatility impacts remain solid, and the R-square increases to 75%. These results are robust to whether the fixed effect or the random effect is taken into account. More importantly, both volatility and jump risk measures show strong nonlinear effects, which suggests that the practice of using aggregate volatility across board or within rating groups could either overestimated or underestimate the true impact from individual firms. Finally, but not least, jump and volatility risks interact prominently with rating groups and firm-specific accounting variables. This evidence indicates that the strong predictability of jump and volatility risks is not merely a statistical phenomenon, rather, it reflects the financial market assessment of firms' economic value and financial health. In particular, the interaction between volatility & jump risks and the quoted recovery rate suggests that credit default spreads have priced in the time-varying recovery risk. These findings are consistent with a limited simulation exercise from stylized structural models, and may help to resolve the so-called credit premium puzzle.

The remainder of the paper is organized as follows. Section 2 introduces the methodology for disentangling volatility and jump risks with high frequency data. Section 3 gives a brief discussion about the credit default swap data and the structural explanatory variables. Section 4 presents the main empirical findings regarding jump and volatility risks in explaining the credit spreads. Some further discussion in supporting the empirical results is included in Section 5, along with a limited simulation exercise illustrating the relationship between credit spreads and equity volatility. Section 6 concludes.

2 Disentangling jump and volatility risks

Equity volatility is central to asset pricing and risk management. Traditionally, researchers have used the historical volatility measure, which are constructed from daily returns. A daily return r_t is defined as the first difference between the log closing prices on consecutive trading days, that is

$$r_t \equiv \log P_t - \log P_{t-1} \tag{1}$$

Historical volatility, defined as the standard deviation of the daily return series over a given time horizon, is considered as a proxy for the volatility risk of the underlying asset value process (see, e.g., Campbell and Taksler, 2003).

In recent years, given the increased availability of high-frequency financial data, a number of scholars, including Andersen and Bollerslev (1998), Andersen et al. (2001, 2005), Barndorff-Nielsen and Shephard (2002a,b), and Meddahi (2002), have advocated the use of so-called realized volatility measures by utilizing the information in the intra-day data for measuring and forecasting volatilities. More recent work on bi-power variation measures, which are developed in a series of papers by Barndorff-Nielsen and Shephard (2003a,b, 2004), allows the use of high-frequency data to disentangle realized volatility into continuous and jump components, as in Andersen et al. (2004) and Huang and Tauchen (2004). In this paper, we rely on the stylized fact that jumps on financial markets are rare and of large size, to explicitly estimate the jump intensity, jump variance, and jump mean (positive and negative), and to assess more explicitly the impacts of volatility and jump risks on credit spreads.

Let p_t denote the time t logarithmic price of the asset, and it evolves in continuous time as a jump diffusion process:

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t \tag{2}$$

where μ_t and σ_t are the instantaneous drift and volatility, W_t is the standard Brownian motion, dq_t is a Poisson jump process with intensity λ_J, and κ_t refers to the size of the corresponding (log) jump, which is assumed to be normally distributed with mean μ_J and variance σ_J^2. Note that all these jump parameters are allowed to be time-varying. Time is measured in daily units and the intra-day returns are defined as follows:

$$r_{t,j} \equiv p_{t,j\cdot\Delta} - p_{t,(j-1)\cdot\Delta} \tag{3}$$

where $r_{t,j}$ refers to the j^{th} within-day return on day t, and Δ is the sampling frequency.[2]

Barndorff-Nielsen and Shephard (2003a,b, 2004) propose two general measures to the quadratic variation process, realized volatility and realized bipower variation, which converge uniformly (as $\Delta \to 0$) to different quantities of the jump-diffusion process,

$$\mathrm{RV}_t \equiv \sum_{j=1}^{1/\Delta} r_{t,j}^2 \to \int_{t-1}^{t} \sigma_s^2 ds + \sum_{j=1}^{1/\Delta} \kappa_{t,j}^2 \tag{4}$$

$$\mathrm{BV}_t \equiv \frac{\pi}{2} \sum_{j=2}^{1/\Delta} |r_{t,j}| \cdot |r_{t,j-1}| \to \int_{t-1}^{t} \sigma_s^2 ds \tag{5}$$

Therefore the asymptotic difference between realized volatility and bipower variation is zero when there is no jump and strictly positive when there is a jump. A variety of jump detection techniques have been proposed and studied by Barndorff-Nielsen and Shephard (2004), Andersen et al. (2004), and Huang and Tauchen (2004). Here we adopt the ratio test statistics used by Huang and Tauchen (2004),

$$\mathrm{RJ}_t \equiv \frac{\mathrm{RV}_t - \mathrm{BV}_t}{\mathrm{RV}_t} \tag{6}$$

When appropriately scaled by its asymptotic variance, $z = \frac{\mathrm{RJ}_t}{\sqrt{\mathrm{Avar}(\mathrm{RJ}_t)}}$ converges to a standard normal distribution.[3] This test has excellent size and power (Huang and Tauchen, 2004), and tells us whether there is a jump occurred during a particular day, and how much the jump component contributes to the total realized volatility, i.e., the ratio of $\sum_{j=1}^{1/\Delta} \kappa_{t,j}^2$ over RV_t.

To gain further insight, we assume that (1) there is at most one jump per day and (2) jump size dominates return on jump days. Following the concept of "significant jumps" by

[2] That is, there are $1/\Delta$ observations on every trading day. Typically the 5-minute frequency is used because more frequent observations might be subject to distortion from market microstructure (Aït-Sahalia et al., 2005; Bandi and Russell, 2005).

[3] See Appendix A for implementation details and Huang and Tauchen (2004) for the finite sample performance of competing jump detection statistics. We also find that using the test level of 0.999 produces the most consistent result. We also use staggered returns in constructing the test statistics, to control for the potential measurement error problem (see Appendix A).

Andersen et al. (2004), we use the following methodology to filter out the daily realized jumps,

$$J_t = \text{sign}(r_t) \times \sqrt{\text{RV}_t - \text{BV}_t} \times \text{I}(z > \Phi_{\alpha}^{-1}) \tag{7}$$

where Φ is the probability of a standard Normal distribution and α is the level of significance chosen as 0.999. This method is consistent with the intuition that jumps on financial markets are rare and large. It enables us to estimate various jump parameters for a given horizon: λ_J as the ratio of the number of jump days over the number of trading days, μ_J as the sample mean of J_t, and σ_J as the sample standard deviation of J_t. Further, μ_J^+ and μ_J^- can be estimated as the sample means of positive J_t and negative J_t, respectively. Tauchen and Zhou (2005) shows that under empirically realistic settings, such a method of identifying realized jumps and estimating jump parameters is accurate and efficient in finite samples, as both the sample size increases and the sampling interval shrinks. Equipped with such a new technique, we are ready to reexamine the impact of jumps on credit spreads.

3 CDS spreads and structural explanatory variables

Throughout this paper we choose to use the CDS premium as a direct measure of credit spreads. Credit default swaps are the most popular instrument in the rapidly-growing credit derivative markets. A CDS provides insurance against the default risk of a reference entity (usually a third party). The protection seller promises to buy the reference bond at its par value when a credit event (including bankruptcy, obligation acceleration, obligation default, failure of payment, repudiation or moratorium, or restructuring) occurs. In return, the protection buyer makes periodic payments to the seller until the maturity date of the CDS contract or until a credit event occurs. This periodic payment, which is usually expressed as a percentage (in basis points) of its notional value, is called CDS spread. Ideally, credit spread is a pure measure of the default risk of the reference entity.[4]

Compared with corporate bond spreads, which were widely used in previous studies in this area, CDS spreads have several advantages. First, CDS spread is a relatively pure pricing of default risk of the underlying entity. The contract is typically traded on standardized terms. By contrast, bond spreads are more likely to be affected by differences in contractual

[4]There has been a growing interest in examining the pricing determinants of credit derivative and bond markets (Cossin and Hricko, 2001; Houweling and Vorst, 2005) and the role of the CDS spreads in forecasting future rating events (Hull et al., 2003; Norden and Weber, 2004).

arrangements, such as the seniority, coupon rates, embedded options and guarantees. Second, Longstaff et al. (2005) find that a large proportion of bond spreads are determined by liquidity factors, which do not necessary reflect the default risk of the underlying asset. Third, Blanco et al. (2005) and Zhu (2004) show that, while in the long run CDS spreads and bond spreads are quite in line with each other, in the short run the CDS spreads tend to respond more quickly to changes in credit conditions. This could be partly attributed to the fact that CDS is unfunded and does not face the short-sale restriction. Finally, using CDS spread can avoid the confusion on which proxy to be used as risk-free rates, since they are already quoted as the differences above swap rates.[5]

3.1 CDS spreads

The CDS data are provided by Markit, a comprehensive data source that assembles a network of industry-leading partners who contribute information across several thousand credits. Based on the contributed quotes on each day, Markit creates the daily composite quote for each contract.[6] Together with the pricing information, the dataset also reports the information on the reference entity (name, ratings, industry classification and geographic location), the terms of the contract (maturity, seniority, currency denomination and restructuring clauses)[7], and average recovery rates used by data contributors in pricing each contract.

In this paper we include all CDS quotes written on US entities (sovereign entities excluded) and denominated in US dollars. We eliminate the subordinated class of contracts because of their small relevance in the database and unappealing implication in credit risk pricing. We focus on 5-year CDS contracts with modified restructuring (MR) clause as they are the most popularly traded in the market. After matching the CDS data with other information such as equity prices and balance sheet information (discussed below), we are left with 307 entities in our study. The much larger pool of constituent entities relative to previous studies makes us more comfortable in interpreting our empirical results.

[5]Researchers have used Treasury rates, swap rates and repo rates as proxies for risk-free rates in calculating bond spreads.

[6]Three major filtering criteria are adopted to remove potential measurement errors: (i) an outlier criteria that removes quotes that are far above or below the average prices reported by other contributors; (ii) a staleness criteria that removes contributed quotes that do not change for a very long period; and (iii) a term structure criteria that removes flat curves from the dataset.

[7]There are four major types of restructuring clauses: full restructuring, modified restructuring, modified-modified restructuring and no-restructuring. They differ mainly on the definition of credit events and the pool of deliverable assets if a credit event occurs. See Packer and Zhu (2005) for discussion on the pricing implication of restructuring clauses.

Our sample coverage starts from January 2001 and ends on December 2003. For each of the 307 reference entities, we create the monthly CDS spread by calculating the average composite quote in each month, and similarly, the monthly recovery rates linked to CDS spreads.[8] To avoid measurement errors we remove those observations for which there exist huge discrepancies (above 20%) between CDS spreads with modified-restructuring clauses and those with full-restructuring clauses. In addition, we also remove those CDS spreads that are higher than 20%, because those very high CDS spreads can be spurious for two reasons. First, liquidity tends to dry up when entities are very close to default, therefore the data are less reliable. Second, under this situation trading is more likely to be involved with an upfront payment that is not included in the spreads, so CDS premium is not an accurate reflection of the embedded default risk.

3.2 Structural variables that determine credit spreads

Structural models provide an intuitive framework for identifying the determinants of credit risk changes. A firm defaults whenever the firm value hits below an exogenously or endogenously determined default boundary. Therefore the default probability of the firm is determined by all factors that affect the firm value process, the risk-free interest rate, firm leverage, default boundary and recovery rates. Accordingly, our explanatory variables can be grouped into three major groups: (i) firm-level equity volatility and jump; (ii) firm's balance sheet information; and (iii) macro-financial variables. Theoretic predictions of the impact of these variables on credit spreads based on standard structural models are listed in Table 1.

(i) Individual volatility and jump

We use two sets of measures for equity volatility of individual firms: historical volatility calculated from daily equity price and realized volatility calculated from intra-day equity prices. Data sources are CRSP and TAQ (Trade and Quote), respectively. CRSP provides daily equity prices that are listed in the US stock market, and TAQ includes intra-day (tick-by-tick) transactions data for securities listed on the NYSE, AMES and NASDAQ.

[8] Although composite quotes are available on a daily basis, we choose the data frequency as monthly for two major reasons. First, balance sheet information is available only on a quarterly basis. Using daily data is very likely to miss the impact of firms' balance sheets on CDS pricing. Second, as most CDS contracts are not frequently traded, the CDS dataset suffers a lot from the sparseness problem if we choose daily frequency, particularly in the early sample period. A consequence of the choice of monthly frequency is that there is no obvious autocorrelation in the data set, so the standard OLS regression is a suitable tool in our empirical analysis.

Based on the daily equity prices we calculate historical volatility, historical skewness and historical kurtosis for the 307 reference entities over the 1-month, 3-month and 1-year time horizon, respectively. Similarly, realized volatility (RV) over the same time horizons are calculated following the definition in equation (4). Realized volatility is then further decomposed into the continuous and jump components on a daily basis using the ratio statistics based on equation (6) with the test level of 99.9% (see Appendix A for implementation detail). Finally, using the daily actual jumps identified by equation (7), we are able to calculate the average jump intensity, jump mean and jump standard deviation in a month, a quarter and a year.

(ii) Firms' balance sheet information

The firm-level accounting information is obtained from Compustat. Since it is reported on a quarterly basis, the last available quarterly observations are used to estimate monthly figures. We include the firm leverage ratio, return on equity (ROE), coverage ratio and dividend payout ratio. They are defined as following (in percentages):

$$\begin{aligned}
Leverage &= \frac{Current\ debt + \ Long\ term\ debt}{Total\ equity\ +\ Current\ debt + \ Long\ term\ debt} \\
ROE &= \frac{Pre\ tax\ income}{Total\ equity} \\
Coverage\,ratio &= \frac{Operating\ income\ before\ depreciation\ -\ Depreciation}{Interest\ expense\ +\ Current\ Debt} \\
Dividend\,payout\,ratio &= \frac{Dividend\,payout\,per\,share}{Equity\,price}
\end{aligned}$$

(iii) Macro-financial variables

Following the prevalent practice in existing literature, we also include the following macro-financial variables as explanatory variables of credit spreads: (i) The S&P 500 average daily return, and its volatility (in standard deviation term) in the past twelve months, which proxy for the overall state of the economy; (ii) 3-Month Treasury rate; (iii) The slope of the yield curve, which is defined as the difference between the 10-year and 3-month US Treasury rates. The data are collected from Bloomberg.

3.3 Summary statistics

The upper part of Table 2 summarizes the industry and rating distributions of our sample companies. Overall they are evenly distributed across different sectors, but the ratings are highly concentrated in the single-A and triple-B categories (combined 73% of total). High-yield names represent only 20% of total observations, reflecting the fact that CDS on investment-grade names is still dominating the market.

Table 2 also reports summary statistics of firm-specific accounting and macro-financial variables. The average credit spread is 172 basis points for the 5-year CDS contracts, which also exhibit substantial time variations and cross-section differences. Typically CDS spreads increased substantially in mid-2002, and then declined gradually throughout the remaining sample period, as shown in Figures 1 and 2. By rating categories the average CDS spread for single-A to triple-A entities is 45 basis point, whereas the average spreads for triple-B and high-yield names are 116 and 450 basis points, respectively.

The summary statistics of firm-level volatilities are reported in Table 3.[9] The average daily return volatility (annualized) is between $40 - 50\%$, which is quite consistent by both historical and realized measures. The two volatility measures are also highly correlated (the correlation coefficient is about 0.9). Moreover, based on daily observations, the jump component explains about 8.46% of the total realized variance on average, and contributes about 52.3% on those days with significant jumps (the range is around 40-80% across the 307 entities). In Figure 1 we plot the 1-year historical volatility HV, the 1-month continuous component of realized volatility RV(C) and 1-month jump volatility RV(J) for an individual firm, the General Motors. The credit spread movements seem to be largely affected by the 1-month RV(C). Significant jumps do not occur often but appear to cluster together. Interestingly, jumps appear to be clustered during relative tranquil periods, suggesting that the detected "jumps" are linked to "unexpected" events. Figure 2 plots the same statistics by three rating groups. Obviously, high-yield entities are much more volatile, but there is no obvious distinction within the investment-grade category. However, jump volatility RV(J) does exhibit some differences between the BBB rating group and the AAA-to-A rating groups.

Another interesting finding is the very low correlation between jump volatility RV(J) and historical skewness or kurtosis. This looks surprising at first, as both skewness and kurtosis have been proposed as proxies for detecting jumps in asset return processes.[10] On careful examination, this may reflect the inadequacy of both variables in measuring jumps.

[9] Throughout the remaining part of this paper, "volatility" refers to the standard deviation term to distinguish from the "variance" representation.

[10] Skewness is often loosely associated with the existence of jumps in the financial industry, while kurtosis can be formalized as an econometric test of the jump-diffusion process (Drost et al., 1998).

Historical skewness is an indicator of the asymmetry in asset returns. A large and positive skewness means that extreme upward movements are more likely to occur. Nevertheless, skewness is not a sufficient statistics of jumps. For example, if upward and downward jumps are equally likely to occur, then skewness is always zero. On the other hand, jump volatility RV(J) and kurtosis are direct indicators of the existence of jumps in the continuous-time framework, but the fact that both measures are non-negative suggests that they are unable to reflect the direction of jumps, which is crucial in determining the pricing impact of jumps on CDS spreads.[11] Given the caveats of these measures, we further propose the jump intensity, jump mean, and jump volatility measures based on the signed daily jumps in equation (7). These measures can be used together to provide a full picture of the underlying jump risk impact.

4 Empirical evidence

Our empirical work focuses on the influence of equity return volatility and jumps on credit spreads. We first run regressions with only jump and volatility measures. Then we also include other control variables, such as ratings, macro-financial variables and balance sheet information, as predicted by the structural models and evidenced by empirical literature. Further robustness check with fixed effect and random effect does not affect our results qualitatively. We also find strong interaction effect between jump and volatility measures on the one side, and rating variables and firm's accounting information on the other, suggesting that the impact of financial market risk measures is related to the fundamental health of firms' balance sheet. Finally, the apparent nonlinear effect of jump and volatility risks indicates that using aggregate volatility or rating group measures may over- or under- estimate the true impact of volatility and jump on credit spreads.[12]

4.1 Volatility and jump effects on credit spreads

Table 4 reports the main findings of ordinary least squares (OLS) regressions, which explain credit spreads only by different measures of equity return volatility and/or jump measures.

[11]We have also calculated the skewness and kurtosis based on the five-minute returns. The results are similar and therefore not reported in this paper. More importantly, high-frequency measures are not able to get rid of the above shortcomings by definition.

[12]We should emphasize that all the volatility and jump variables as well as firm accounting variables are lagged at least one month. Therefore we are immune from the simultaneity bias that inflates the R-squares.

Regression (1) using 1-year historical volatility alone yields a R-square of 45%, which is higher than the main result of Campbell and Taksler (2003, regression 8 in Table II, R-square 41%) with all volatility, ratings, accounting information, and macro-finance variables combined together. Regression (2) and (3) show that short term realized volatility also explains a significant portion of spread variations, and that combined long-run (1-year HV) and short-run (1-month RV) volatilities gives the best result of R-square at 50%. The signs of coefficients are all correct — high volatility raises credit spread, and the magnitudes are all sensible — a one percentage volatility shock raises the credit spread by about 3 to 9 basis points. The statistical significance will remain even if we put in all other control variables (discussed in the following subsections).

The much higher explanatory power of equity volatility may be partly due to the gains from using CDS spreads, since bond spreads (used in previous studies) have a larger non-default-risk component. However, our study is distinct from previous studies by including the short-term equity volatility. In combination with the long-run volatility, it gives a rough indicator on the stochastic movement in equity volatility. The significant gains in the explanatory power seem to support the view that the time variation in volatility, an issue largely ignored in the existing literature on credit risk, is important in determining credit spreads (see Section 5 for more discussion).

Our major contribution is to construct innovative jump measures and show that jump risks are indeed priced in CDS spreads. Regression (4) suggests that historical skewness as a measure of jump risk can have a correct sign (positive jumps reduce spreads), provided that we also include the historical kurtosis which always has a correct sign (more jumps increases spread). This is in contrast with the counter-intuitive finding that skewness has a significantly positive impact on credit spreads (Cremers et al., 2004b). However, the total predictability of traditional jump measure is still very dismal — only 3% in R-square. Our new measures of jumps — regressions (5) to (7) — give significant estimates, and by themselves explain 23% of credit spread variations. A few points are worth mentioning. First, the jump volatility has the strongest impact — raising default spread by 3-5 basis points for one percentage increase. Second, when jump mean effect (-0.2 basis point) is decomposed into positive and negative parts, there is some asymmetry in that positive jumps only reduce spreads by 0.5 basis point but negative jumps can increase spreads by 1.50 basis points. Hence we will treat the two directions of jumps separately in the remaining part of this paper. Third, average jump size only has a muted impact (-0.2) and jump intensity can switch sign (from 0.7 to -0.6), which may be explained by controlling for positive or negative jumps.

Our new benchmark—regression (8) explains 53% of credit spreads with volatility and jump variables alone. To summarize, both long-run and short-run volatilities have significant positive impacts, so do jump intensity, jump volatility, and negative jump; while positive jump reduces spreads.

4.2 Extended regression with traditional controlling variables

We then include more explanatory variables—credit ratings, macro-financial conditions and firm's balance sheet information—all of which are theoretic determinants of credit spreads and have been widely used in previous empirical studies. The regressions are implemented in pairs, one with and the other without measures of volatility and jump. Table 5 reports the results.

In the first exercise, we examine the extra explanatory power of equity return volatility and jump in addition to ratings. Cossin and Hricko (2001) suggest that rating information is the single most important factor in determinant CDS spreads. Indeed, our results confirm their findings that rating information alone explains about 57% of the variation in credit spreads, about the same as the volatility and jump effects are able to explain (see Table 4). By comparing the rating dummy coefficients, apparently lower-rating entities are priced significantly higher than high-rating ones, which is economically intuitive and consistent with the existing literature. A remarkable result is that, volatility and jump risks can explain another 16% of the variation (R^2 increases to 73%).

The increase in R^2 is also very large in the second pair of regressions. Regression (3) shows that all other variables, including macro-financial factors (market return, market volatility, the level and slope of the yield curve), firm's balance sheet information (ROE, firm leverage, coverage and dividend payout ratio) and the recovery rate used by CDS price providers, combined explain an additional 6% of credit spread movements on the top of rating information (regression (3) versus (1)). The combined impact increase is smaller than the volatility and jump effect (16%). Moreover, regression (4) suggests that the inclusion of volatility and jump effect provides another 12% explanatory power compared to regression (3). R^2 increases to a very high level of 0.75. The results suggest that the volatility effect is independent of the impact of other structural or macro factors.

The jump and volatility effects are very robust, with the same signs and little change in magnitudes. To gauge the economic significance more systemically, it is useful to go back to the summary statistics presented earlier (Table 3). The cross-firm averages of the standard-deviation of the 1-year historical volatility and the 1-month realized volatility (continuous component) are 18.57% and 25.85%, respectively. Such shocks lead to a widening of the credit spreads by almost 46-55 and 42-51 basis points, respectively. For the jump component, a one standard-deviation shock in JI, JV, JP and JN (49.11%, 19.63%, 113.98% and 110.97%) changes the credit spread by about 50, 25, 70 and 35 basis points, respectively. Adding them up, these factors could be able to explain a large component of the cross-sectional difference and temporal variation in credit spreads observed in the data.

Judging from the full model of regression (4), a majority of macro-financial factors and firm variables have the expected signs. The market return has a significant negative impact on the spreads, consistent with the business cycle effect. High leverage ratio and high dividend payout ratio tend to increase credit spread significantly, which is consistent with structural model insight. Other control variables seem to have either marginal t-statistics or economically counter-intuitive signs, and their signs & magnitudes seem to be unstable depending on model specification.

Another observation, which needs to be emphasized, is that the high explanatory power of rating dummies quickly diminished when the macro-financial and firm specific variables are included. The t-ratios of ratings precipitate dramatically from regressions (1) and (2) to regressions (3) and (4), while the t-ratios for jump and volatility measures remain very high. This result is consistent with the practice of rating agencies that rate entities according to their accounting information and macroeconomic condition.

4.3 Robustness Check

We also implement a robustness check by using panel data technique with fixed and random effects (see Table 6). Although Hausman test favors fixed effects over random effects, the regression results do not differ much between these two approaches. In particular, the slope coefficients of the individual volatility and jump variables are remarkably stable and qualitatively unchanged. On the other hand, only some of the macro-financial and firm accountings variables have consistent and significant impacts on credit spreads, including market return (negative), term spread (positive), leverage ratio (positive), and dividend payout (positive). Also of interest is that the R-square can be as high as 87% in the fixed effect panel regression, if we allow firm specific dummies.[13]

4.4 Interaction with rating group and accounting information

We have demonstrated that equity volatility and jump help to determine CDS spreads. There remain questions of whether the effect is merely a statistical phenomenon or intimately related to firm's credit standing and accounting fundamental, and whether the effect is non-linear in nature. The next two sub-sections aim to address these two issues respectively.

We first examine whether the volatility effect varies across different rating groups. Regression (1) in Table 7 examines the interactive effects between volatility and jump measures and three rating groups: triple-A to single-A names, triple-B names and high-yield entities. The results are remarkable in that the volatility/jump impact coefficients from high yield entities are typically several times larger than for the top investment grade names. To be more precise, for long-run volatility the difference is 4.69 over 2.28, short-run volatility 2.53 over 0.37, jump intensity 2.70 over 1.19, jump volatility 3.92 over 0.58, and positive jump -1.08 over -0.24. Similarly the t-ratios of high-yield interaction terms are also much larger than those of the investment grade. If we take into account the fact that high-yield names are associated with much higher volatility and jump risk (Figure 2), the economic implication of the differences in those interactive coefficients is even more remarkable. In addition, these differences seem to be much larger for the realized volatility and jump risk measures, than for the historical volatility measure, which further justifies our approach of identifying volatility and jump risks separately from high frequency data.

Our measures on jumps and volatilities also interact strongly with the firm specific accounting information. The right panel of Table 7 reports all significant coefficients (for regression 2). The combined explanatory power for credit spreads reaches a R-square of 80%. And overall, the results support the view that the pricing impact of volatility and jump risk effect is smaller for those firms with better performance. For example, a higher recovery rate is related to smaller impacts of the long-run volatility effect, the jump volatility effect and positive jump effect. Similarly, for highly-leverage firms, their credit spreads

[13] We have also experimented with the Newey and West (1987) heteroscedasticity and auto-correlation (HAC) robust standard error, which only makes the t-ratios slightly smaller but makes no qualitative differences. This is consistent with the fact that our empirical regressions do not involve overlapping horizons, lagged dependent variables, or contemporaneous regressors that are related to individual firms' return, volatility, and jump measures. The remaining heteroscedasticity is very small given so many firm-specific variables are included in the regressions.

appear to be respond more dramatically to changes in long-run and short-run volatility and negative jumps. Following the same line, the short-term volatility effect is significantly larger for those firms with high payout ratio (the asset value declines and therefore indebtedness increases) and low profitability. One exception is the interactive coefficient between short-term volatility and recovery rates, which turns out to be surprisingly negative. This might be partly due to the dynamic lead-lag relationship between the two variables. To summarize, the above results reinforce the idea that volatility and jump risks are priced in the CDS spreads, not only because there are statistical linkages, but also because equity market trades on the firms' fundamental information.

4.5 Nonlinear effect and credit premium puzzle

While the theory usually implies a complicated relationship between volatility and credit spreads, in empirical exercise a simplified linear relationship is often used. This linear approximation could cause substantial bias in calibration exercise and partly contribute to the under-performance of structural models, or the so-called credit premium puzzle. For instance, in Huang and Huang (2003) paper, they used the average equity volatility within a rating class in their calibration, and found that the predicted credit spread is much lower than the observed value (average credit spreads in the rating class). However, the "averaging" of individual equity volatility could be problematic if its true impact on credit spread in non-linear.

Table 8 confirms the existence of the non-linearity effect of volatility and jump. By adding the squared and cubic terms of the jump and volatility risk measures, we find that most of the nonlinear terms are statistically significant. The sign of each order may not be quite interpretable, since the entire nonlinear function is driving the impact. Figure 3 illustrates the potential impact of this "Jensen inequality" problem, on assessing the performance of structural models in pricing credit risk. The solid lines plot the aggregate pricing impacts of 1-year and 1-month volatility, jump intensity, jump volatility, positive and negative jumps, respectively, with each variable of interest ranging from its 5'th and 95'th percentile distributions.

The argument that the ignorance of the nonlinear effect causes the under-performance of structural models can be clearly illustrated in an example. Consider two firms with 1-year volatility of $HV_1 = 23.73\%$ and $HV_2 = 79.63\%$ respectively (corresponding to the 5'th and 95'th percentile value in the sample), with weights ω_1 and ω_2 so that $\omega_1 HV_1 +$

$\omega_2 HV_2 = 43.62\%$ (43.62% is the sample mean). Suppose that the CDS pricing formula can be represented by $P(HV, \cdots)$. Whereas the average CDS spread should be calculated as $\omega_1 P(HV_1, \cdots) + \omega_2 P(HV_2, \cdots)$, the common practice in model calibration would use $P(\omega_1 HV_1 + \omega_2 HV_2, \cdots)$ instead. Figure 3 shows that the predicted credit spread is 37 basis points lower than the true average credit spread due to this nonlinear effect. Similarly, by using the average 1-month realized volatility rather than individual ones in calibration, the credit spreads can be under-predicted by as much as 14 basis points. The non-linear effect in jump intensity works in the opposite way: it can predict an average credit spread 33 basis points higher than the true one. This is partially cancelled out by the nonlinearity in the jump volatility effect (8 basis points). An interesting observation is the signed jumps — in negative region averaging may under-predict credit spreads but in positive region over-predict, yielding a small over-prediction in aggregate.

In short, averaging volatilities over individual firms produces significant underfitting of credit yield curve, while averaging jumps produces small overfitting. The combined effect of the nonlinearity is indicative to resolve the credit premium puzzle. Although quantitatively, this consideration is still not able to fully reconcile the disparity yet, it can perhaps point us to a promising direction for future research to address this issue.

5 Further discussion on supporting evidence

Our positive findings regarding the predictability of volatility and jump impact on credit spreads may be due to two sources of improvement — better measurement of the jump and volatility risks and more appropriate empirical specification to include them.

In this paper we use a combination of long-run and short-run volatility to measure the volatility risk, and construct a few new measures for different dimensions of the jump risk (jump intensity, jump mean, and jump volatility). The superiority of our jump measures over traditional ones (skewness and kurtosis) has been discussed in Section 3.3 and will be skipped here. In addition, there are two justifications for choosing those volatility variables. First, in most structural models, asset volatility rather than equity volatility is the appropriate concept to use in pricing the credit derivatives. Since asset volatility is not directly observable, empirical work (including ours) has to go for equity volatility. Existing literature usually adopts the long-term equity volatility, with an implicit assumption that equity volatility is constant over time. However, this assumption is inconsistent with the prediction from structural models. Note for instance that within the Merton (1974) model, although the asset value volatility is constant, the equity volatility is still time-varying, because the time-varying asset value generates time-variation in the non-linear delta function. Within the stochastic volatility model (as discussed below), equity volatility is time-varying because both the asset volatility and the asset value are time-varying. Therefore, a combination of both long-run and short-run volatility could be used to reflect the time-variation in equity volatility, which has often been ignored in the past. Second, whereas structural models typically stipulate that *expected* volatility matters, in this paper we use lagged variables. This is supported by the recent findings in Andersen et al. (2004). They show that including lagged realized volatility of different time horizons, particularly when jump measures are added as additional explanatory variables, one can significantly improve the volatility forecasting accuracy. Therefore, the use of lagged variables can be considered as a reduced-form *expectation* of future volatility.

The inclusion of jumps measure in explaining credit spreads is also supported by the simulation analysis by Zhou (2001). Following Merton (1976), Zhou (2001) introduces a jump component into the standard credit pricing framework, and simulates the relationship between credit spreads and jump characteristics. In particular, he shows that credit spreads increase with jump intensity and jump volatility, which are consistent with our empirical results. Zhou (2001) also suggests that because the presence of potential jumps, the credit spreads for very short maturities can be significantly higher than zero, which is a confounding challenge for standard structural models in explaining the investment grade names. We move even further to explore the interactive effect between the jump component and firm value fundamentals and to document explicitly the nonlinear impact of jump impact on credit spreads, two issues that have not been well studied within a stylized structural framework.

Furthermore, our model specifications in Tables 7 and 8, in which interactive terms and nonlinear terms are included, and their high explanatory power, are also qualitatively consistent with the structural model implications. In Appendix B we describe a simulation exercise that allows us to examine the capability of a standard model of Merton (1974) and a stochastic volatility model, one of the specifications examined by Huang (2005), in replicating the forecast-ability of historical equity volatility for credit premium. Based on the simulated time series we perform regression analysis between current month credit spread and lagged one year & one month volatility of equity, nonlinear volatility term, and an interaction term of equity volatility and asset value change (i.e. firm leverage). The results are shown in

Table 9.

It is clear that even with the Merton (1974) model, 1-year and 1-month equity volatility and volatility squared show strong predictability for credit risk premia, with R-square between 0.53, 0.57 and 0.53, and positive signs largely consistent with our empirical findings. Also note that the interaction term of long-run equity volatility and firm value change is negatively impacting the credit spreads, which is also consistent with our empirical evidence in Table 7 on historical volatility and recovery rate. It should be point out that within the Merton (1974) model the asset volatility is constant. However the equity volatility is time-varying due to the fact that the nonlinear delta function depends on the time-varying firm value. Our justification of time-varying volatility effect on credit spread is completely opposite to that of Campbell and Taksler (2003), who assume that debt is risk-free and that delta function is constant.

As seen from Table 9, a stochastic volatility model produces similar predictability R-squares and coefficient signs, for the default risk premium from long-run and short-run equity volatility, nonlinear term, and interaction term. However, coefficient magnitudes are 2-10 times larger than the constant volatility model, and t-ratios of parameter estimates are also higher than the Merton (1974) model. Both the nonlinear and the interaction terms have similar sign as we discovered in the empirical exercise. Also, the R-square of 0.34-0.55 from volatility and R-square of 0.72 from jointly volatility and interaction combined, match quite well with what we have found in the actual CDS prediction regressions.

The simulation results also demonstrate the flexibility of credit yield curves from the time-varying volatility models. Figure 4 illustrates the difference between the credit yield curves from a stochastic volatility model and the Merton (1974) model. In the benchmark case (upper left), both models have the same unconditional volatility. The credit curve from Merton (1974) model is very flat. In contrast, in the stochastic volatility model, the levels of credit spreads are much higher and the yield curve much steeper up to the one year maturity. By changing the underlying model parameters, the credit curve from time-varying volatility model can assume a variety of shapes—flat, steep, hump, straight, etc.. Such a flexibility may potentially overcome the under-fitting problem of standard structural models, and may price the individual credit spread more accurately. This, nevertheless, remains a very challenging task to be accomplished in future research.

6 Conclusions

In this paper we use a large dataset to examine the impact of theoretic determinants, particularly firm-level equity return volatility and jumps, on the level of credit spreads in the credit-default-swap market. Our results find strong volatility and jump effect, which predict another 16% of the movements in credit spreads after controlling for rating information and other structural factors. In particular, when all these control variables are included, equity volatility and jumps are still the most significant factors, even more so than the rating dummy variables. This effect is economically significant and remains robust to a number of variants of the estimation method. The volatility and jump effects are the strongest for high-yield entities and those financially-stressed firms. Furthermore, the volatility and jump effects exhibit strong non-linearity, which can partially explain the under-performance of structural models in the existing literature.

We adopt an innovative approach to identify equity jumps of individual firms, which enables us to assess the impact of various jump risks (intensity, variance, negative jumps) on default risk premia. Our results on jumps are statistically and economically significant, which contrasts the typical mixed finding in literature using historical or implied skewness as jump proxy.

Our study is only a first step towards improving our understanding of the impact of volatility and jumps on credit risk market. Calibration exercise that takes into account the time variation of volatility & jump risks and the non-linear effect could be a promising direction to explore for resolving the so-called credit premium puzzle. Related issues, such as the connections between equity volatility and asset volatility, are also worth more attention from both academic researchers and market practitioners.

References

Aït-Sahalia, Yacine, Per A. Mykland, and Lan Zhang (2005), "How often to sample a continuous-time process in the presence of market microstructure noise," *Review of Financial Studies*, vol. 18, 351–416.

Amato, Jeffrey and Eli Remolona (2003), "The credit premium puzzle," *BIS Quarterly Review*, vol. 2003-4, 51–63.

Andersen, Torben G. and Tim Bollerslev (1998), "Answering the skeptics: yes, standard volatility models do provide accurate forecasts," *International Economic Review*, vol. 39, 885–905.

Andersen, Torben G., Tim Bollerslev, and Francis X. Diebold (2004), "Some like it smooth, and some like it rough: untangling continuous and jump components in measuring, modeling, and forecasting asset return volatility," *Working Paper*, Duke University.

Andersen, Torben G., Tim Bollerslev, and Francis X. Diebold (2005), *Handbook of Financial Econometrics*, chap. Parametric and nonparametric volatility measurement, Elsevier Science B.V., Amsterdam.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Paul Labys (2001), "The distribution of realized exchange rate volatility," *Journal of the American Statistical Association*, vol. 96, 42–55.

Anderson, Ronald W., Suresh Sundaresan, and Pierre Tychon (1996), "Strategic analysis of contingent claims," *European Economic Review*, vol. 40, 871–881.

Bandi, Federico M. and Jeffrey R. Russell (2005), "Separating microstructure noise from volatility," *Working Paper*, university of Chicago.

Barndorff-Nielsen, Ole and Neil Shephard (2002a), "Econometric analysis of realized volatility and its use in estimating stochastic volatility models," *Journal of the Royal Statistical Society*, vol. 64, 253–280.

Barndorff-Nielsen, Ole and Neil Shephard (2002b), "Estimating quadratic variation using realized variance," *Journal of Applied Econometrics*, vol. 17, 457–478.

Barndorff-Nielsen, Ole and Neil Shephard (2003a), "Econometrics of testing for jumps in financial economics using bipower variation," *Working Paper*, Oxford University.

Barndorff-Nielsen, Ole and Neil Shephard (2003b), "Realised power variation and stochastic volatility," *Bernoulli*, vol. 9, 243–165.

Barndorff-Nielsen, Ole and Neil Shephard (2004), "Power and bipower variation with stochastic volatility and jumps," *Journal of Financial Econometrics*, vol. 2, 1–48.

Blanco, Roberto, Simon Brennan, and Ian W. March (2005), "An empirical analysis of the dynamic relationship between investment-grade bonds and credit default swaps," *Journal of Finance*, vol. 60, forthcoming.

Campbell, John and Glen Taksler (2003), "Equity volatility and corporate bond yields," *Journal of Finance*, vol. 58, 2321–2349.

Collin-Dufresne, Pierre and Robert Goldstein (2001), "Do credit spreads reflect stationary leverage ratios?" *Journal of Finance*, vol. 56, 1929–1957.

Collin-Dufresne, Pierre, Robert Goldstein, and Jean Helwege (2003), "Is credit event risk priced? Modeling contagion via the updating of beliefs," *Working Paper*, Carnegie Mellon University.

Collin-Dufresne, Pierre, Robert Goldstein, and Spencer Martin (2001), "The determinants of credit spread changes," *Journal of Finance*, vol. 56, 2177–2207.

Cossin, Didier and Tomas Hricko (2001), "Exploring for the determinants of credit risk in credit default swap transaction data," *Working Paper*.

Cremers, Martijn, Joost Driessen, Pascal Maenhout, and David Weinbaum (2004a), "Explaining the level of credit spreads: option-implied jump risk premia in a firm value model," *Working Paper*, Cornell University.

Cremers, Martijn, Joost Driessen, Pascal Maenhout, and David Weinbaum (2004b), "Individual stock-option prices and credit spreads," *Yale ICF Working Paper*, Yale School of Management.

Drost, Feike C., Theo E. Nijman, and Bas J. M. Werker (1998), "Estimation and testing in models containing both jumps and conditional heteroskedasticity," *Journal of Business and Economic Statistics*, vol. 16, 237–243.

Eom, Young Ho, Jean Helwege, and Jingzhi Huang (2004), "Structural models of corporate bond pricing: an empirical analysis," *Review of Financial Studies*, vol. 17, 499–544.

Heston, Steven (1993), "A closed-form solution for options with stochastic volatility with applications to bond and currency options," *Review of Financial Studies*, vol. 6, 327–343.

Houweling, Patrick and Ton Vorst (2005), "Pricing default swaps: empirical evidence," *Journal of International Money and Finance*.

Huang, Jingzhi (2005), "Affine structural models of corporate bond pricing," *Working Paper*, Penn State University.

Huang, Jingzhi and Ming Huang (2003), "How much of the corporate-treasury yield spread is due to credit risk?" *Working Paper*, Penn State University.

Huang, Xin and George Tauchen (2004), "The relative contribution of jumps to total price variance," *Working Paper*, Duke University.

Hull, John, Mirela Predescu, and Alan White (2003), "The relationship between credit default swap spreads, bond yields, and credit rating announcements," *Journal of Banking and Finance*, vol. 28, 2789–2811.

Kassam, Altaf (2003), "Options and volatility," *Goldman Sachs Derivatives and Trading Research Report*.

Leland, Hayne E. (1994), "Corporate debt value, bond covenants, and optimal capital structure," *Journal of Finance*, vol. 49, 1213–1252.

Leland, Hayne E. and Klaus B. Toft (1996), "Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads," *Journal of Finance*, vol. 51, 987–1019.

Longstaff, Francis, Sanjay Mithal, and Eric Neis (2005), "Corporate yield spreads: default risk or liquidity? new evidence from the credit-default-swap market," *Journal of Finance*, (forthcoming).

Longstaff, Francis and Eduardo Schwartz (1995), "A simple approach to valuing risky fixed and floating rate debt," *Journal of Finance*, vol. 50, 789–820.

Meddahi, Nour (2002), "A theoretical comparison between integrated and realized volatility," *Journal of Applied Econometrics*, vol. 17.

Mella-Barral, Pierre and William Perraudin (1997), "Strategic debt service," *Journal of Finance*, vol. 52, 531–566.

Merton, Robert (1974), "On the pricing of corporate debt: the risk structure of interest rates," *Journal of Finance*, vol. 29, 449–470.

Merton, Robert C. (1976), "Option pricing when underlying stock returns are discontinuous," *Journal of Financial Economics*, vol. 3, 125–144.

Newey, Whitney K. and Kenneth D. West (1987), "A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica*, vol. 55, 703–708.

Norden, Lars and Martin Weber (2004), “Informational efficiency of credit default swap and stock markets: the impact of credit rating announcements,” *CEPR Discussion Paper Series*.

Packer, Frank and Haibin Zhu (2005), “Contractual terms and CDS pricing,” *BIS Quarterly Review*, vol. 2005-1, 89–100.

Tauchen, George and Hao Zhou (2005), “Identifying realized jumps on financial markets,” *Working Paper*, Federal Reserve Board.

Zhou, Chunsheng (2001), “The term structure of credit spreads with jump risk,” *Journal of Banking and Finance*, vol. 25, 2015–2040.

Zhu, Haibin (2004), “An empirical comparison of credit spreads between the bond market and the credit default swap market,” *BIS Working Paper*.

Appendix

A Test statistics of daily jumps

Barndorff-Nielsen and Shephard (2004) and Huang and Tauchen (2004) adopt a test statistics of significant jumps based on the ratio statistics as defined in equation (7),

$$z = \frac{\mathrm{RJ}_t}{[((\pi/2)^2 + \pi - 5) \cdot \Delta \cdot \max(1, \frac{\mathrm{TP}_t}{\mathrm{BV}_t^2})]^{1/2}} \tag{8}$$

where Δ and BV_t are defined as in Section 2 and

$$\mathrm{TP}_t \equiv \frac{1}{4\Delta[\Gamma(7/6) \cdot \Gamma(1/2)^{-1}]^3} \cdot \sum_{j=3}^{1/\Delta} |r_{t,j}|^{4/3} \cdot |r_{t,j-1}|^{4/3} \cdot |r_{t,j-2}|^{4/3}$$

When $\Delta \to 0$, $\mathrm{TP}_t \to \int_{t-1}^{t} \sigma_s^4 ds$ and $z \to N(0,1)$. Hence daily "jumps" can be detected by choosing different levels of significance.

In implementation, Huang and Tauchen (2004) suggest to use staggered returns to break the correlation in adjacent returns, an unappealing phenomenon caused by the microstructure noise. In this paper we follow this suggestion and use the following generalized bipower measures ($i = 1$):

$$\begin{aligned} \mathrm{BV}_t &\equiv \frac{\pi}{2} \sum_{j=2+i}^{1/\Delta} |r_{t,j}| \cdot |r_{t,j-(1+i)}| \\ \mathrm{TP}_t &\equiv \frac{1}{4\Delta[\Gamma(7/6) \cdot \Gamma(1/2)^{-1}]^3} \cdot \sum_{j=1+2(1+i)}^{1/\Delta} |r_{t,j}|^{4/3} \cdot |r_{t,j-(1+i)}|^{4/3} \cdot |r_{t,j-2(1+i)}|^{4/3} \end{aligned}$$

Following Andersen et al. (2004), the continuous and jump components of realized volatility on each day are defined as

$$\mathrm{RV(J)}_t = \sqrt{\mathrm{RV}_t - \mathrm{BV}_t} \cdot \mathrm{I}(z > \Phi_\alpha^{-1}) \tag{9}$$

$$\mathrm{RV(C)}_t = \sqrt{\mathrm{RV}_t} \cdot [1 - \mathrm{I}(z > \Phi_\alpha^{-1})] + \sqrt{\mathrm{BV}_t} \cdot \mathrm{I}(z > \Phi_\alpha^{-1}) \tag{10}$$

where RV_t is defined by equation (4), $\mathrm{I}(\cdot)$ is an indicator function and α is the chosen significance level. Based on the Monte Carlo evidence in Huang and Tauchen (2004) and Tauchen and Zhou (2005), we choose the significance level α as 0.999 with adjustment for microstructure noise.

B Simulations based on a structural model with time-varying volatility

Given constant risk-free rate r and constant default boundary K, firm value process V_t with stochastic volatility σ_t,

$$\frac{dV_t}{V_t} = (\mu_t - \delta)dt + \sigma_t dW_{1t} \tag{11}$$

$$d\sigma_t^2 = \beta(\alpha - \sigma_t^2)dt + \gamma\sigma_t dW_{2t} \tag{12}$$

where the innovations in value and volatility processes are correlated as $\text{corr}(dW_{1t}, dW_{2t}) = \rho dt$. Existing model usually assumes stochastic interest rate and time varying leverage, but keeps the volatility constant. Assuming that all assets are traded and no-arbitrage implies the existence of an equivalent martingale measure,

$$\frac{dV_t}{V_t} = (r - \delta)dt + \sigma_t dW_{1t}^* \tag{13}$$

$$d\sigma_t^2 = \beta^*(\alpha^* - \sigma_t^2)dt + \gamma\sigma_t dW_{2t}^* \tag{14}$$

with volatility risk premium ξ, such that $\beta^* = \beta + \xi$ and $\alpha^* = \beta\alpha/\beta^*$. Equity price S_t of the firm can be viewed as an European call option with matching maturity T for debt D_t with face value K. The solution is given by Heston (1993),

$$S_t = V_t P_1^* - Ke^{-r(T-t)}P_2^* \tag{15}$$

where P_1^* and P_2^* are risk-neutral probabilities. In the context of Merton (1974) model, these probabilities are from normal distributions with a constant asset volatility parameter $\sigma_t^2 = \alpha$, i.e., $S_t = V_t N_1^* - Ke^{-r(T-t)}N_2^*$. Therefore the debt value of both models can be expressed as $D_t = V_t - S_t$, and its price is $P_t = D_t/K$. The credit default spread is given by

$$R_t - r = -\frac{1}{T-t}\log(P_t) - r \tag{16}$$

In simulations, we set the parameters as following: $\beta = 0.10$, $\alpha = 0.25$, $\gamma = 0.10$, $\xi = -0.20$, and $\rho = -0.50$. To focus on stochastic volatility, we set non-essential parameters to zero, i.e., $\mu_t = \delta = r = 0$. In addition, the starting value of the asset is set at 100 and the debt boundary is set at 60. For each random sample, we simulate 10 years of daily realization, and then calculate the monthly variables similar to the empirical exercise. We perform regression analysis between current month credit spread and lagged 1-year volatility, 1-month volatility, volatility squared, and interactions including volatility and asset value change. The total Monte Carlo replications is 2000. The results are shown in Table 9.

Table 1: **Theoretic prediction of the impact of structural factors on credit spreads**

Variables	**Impacts**	**Economic intuitions**
Equity return	Negative	A higher growth in firm value reduces the probability of default (PD).
Equity volatility	Positive	Higher equity volatility often implies higher asset volatility, therefore the firm value is more likely to hit below the default boundary.
Equity skewness	Negative	Higher skewness means more positive returns than negative ones.
Equity kurtosis	Positive	Higher kurtosis means more extreme movements in equity returns.
Jump component		Zhou (2001) suggests that credit spreads increase in jump intensity and jump variance (more extreme movements in asset returns), and decrease in the mean of jump size as it implies that more positive returns are likely to occur.
Firm leverage	Positive	The Merton (1974)'s framework predicts that a firm defaults when its leverage ratio approaches one. Hence credit spreads increase with leverage.
ROE	Negative	PD is lower when the firm's profitability improves.
Coverage ratio	Negative	It measures the firm's ability to pay back its outstanding debt.
Dividend payout ratio	Positive	A higher dividend payout ratio means a decrease in asset value, therefore a default is more likely to occur.
General market return	Negative	Higher market returns indicate an improved economic environment.
General market volatility	Positive	Economic conditions are improved when market volatility is low.
Short-term interest rate	Ambiguous	A higher spot rate increases the risk-neutral drift of the firm value process and reduces PD (Longstaff et al., 2005). Alternatively, it may reflect a tightened monetary policy stance and therefore PD increases.
Slope of yield curve	Ambiguous	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 rising inflation rate and monetary tightening of credit.
Recovery rates	Negative	Higher recovery rates reduces the present value of protection payments in the CDS contract.

Table 2: **Summary Statistics:** (upper left) sectoral distribution of sample entities; (upper right) distribution of credit spread observations by ratings; (lower left) firm-specific information; (lower right) macro-financial variables.

By sector	**number**	**percentage (%)**	**By rating**	**number**	**percentage (%)**
Communications	20	6.51	AAA	219	2.15
Consumer cyclical	63	20.52	AA	559	5.48
Consumer Stable	55	17.92	A	3052	29.92
Energy	27	8.79	BBB	4394	43.07
Financial	23	7.49	BB	1321	12.95
Industrial	48	15.64	B	544	5.33
Materials	35	11.40	CCC	112	1.10
Technology	14	4.56			
Utilities	18	5.88			
Not specified	4	1.30			
Total	*307*	*100*	*Total*	*10201*	*100*
Firm-specific variables	**Mean**	**Std. dev.**	**Macro-financial variables**	**Mean (%)**	**Std. dev.**
Recovery rates (%)	39.50	4.63	S&P 500 return	-13.15	14.72
Return on equity (%)	4.50	6.80	S&P 500 vol	22.42	2.90
Leverage ratio (%)	48.81	18.64	3-M Treasury rate	2.04	1.24
Coverage ratio (%)	125.94	209.18	Term spread	2.51	0.96
Div. Payout ratio (%)	0.41	0.47			
5-year CDS spread (bps)	172	230			
1-year CDS spread (bps)	157	236			

Table 3: **Summary statistics of equity returns**

2.A Historical measures (%)						
Variables	*1-month*		*3-month*		*1-year*	
	mean	*std dev*	*mean*	*std dev*	*mean*	*std dev*
Hist ret	3.12	154.26	1.58	87.35	-3.22	42.70
Hist vol (HV)	38.35	23.91	40.29	22.16	43.62	18.57
Hist skew (HS)	0.042	0.75	-0.061	0.93	-0.335	1.22
Hist kurt (HK)	3.36	1.71	4.91	4.25	8.62	11.78

2.B Realized measures (%)						
Variables	*1-month*		*3-month*		*1-year*	
	mean	*std dev*	*mean*	*std dev*	*mean*	*std dev*
RV	45.83	25.98	47.51	24.60	50.76	22.49
RV(C)	44.20	25.85	45.96	24.44	49.37	22.25
RV(J)	7.85	9.59	8.60	8.88	9.03	8.27

2.C Correlations			
Variables	*1-month*	*3-month*	*1-year*
(HV, RV)	0.87	0.90	0.91
(HV, RV(C))	0.87	0.89	0.90
(HS, RV(J))	0.006	0.014	0.009
(HK, RV(J))	0.040	0.025	0.011

Notes: (1) Throughout all the tables, historical volatility HV, realized volatility RV and its continuous RV(C) and jump RV(J) components are represented by their standard deviation terms; (2) The continuous and jump components of realized volatility are defined at a significance level of 99.9% (see Appendix A).

Table 4: **Baseline regression: explaining 5-year CDS spreads using individual equity volatilities and jumps**

	Dependent variable: 5-year CDS spread (in basis point)							
Explanatory variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Constant	-207.22	-91.10	-223.11	147.35	169.29	85.66	20.80	-273.46
	(36.5)	(18.4)	(40.6)	(39.6)	(50.3)	(20.8)	(3.9)	(42.8)
1-year HV	9.01		6.51					6.90
	(72.33)		(40.2)					(38.8)
1-year HS				-10.23				
				(3.2)				
1-year HK				2.59				
				(7.5)				
1-month RV		6.04	2.78					
		(60.5)	(23.0)					
1-month RV(C)								2.37
								(20.2)
1-year JI					0.71		-0.65	1.46
					(9.5)		(5.0)	(13.4)
1-year JM					-0.21			
					(15.8)			
1-year JV					5.21		3.44	1.20
					(32.9)		(14.4)	(6.3)
1-year JP						-0.45	-0.67	-0.62
						(7.3)	(9.8)	(11.8)
1-year JN						1.47	1.56	0.45
						(22.9)	(23.6)	(8.3)
Adjusted R^2	0.45	0.37	0.50	0.03	0.19	0.14	0.23	0.53
Obs.	6342	6353	6337	6342	6064	6328	6064	6064

Notes: (1) t-statistics in the parenthesis; (2) JI, JM, JV, JP and JN refer to the jump intensity, jump mean, jump standard deviation, positive jumps and negative jumps as defined in Section 2.

Table 5: **Regressions with ratings, individual equity volatilities & jumps, macro-financial variables, firm-specific variables and recovery rates**

Regression	**1**		**2**		**3**		**4**	
	coef	*t-stat*	*coef*	*t-stat*	*coef*	*t-stat*	*coef*	*t-stat*
1-year Return			-0.81	(17.5)			-0.67	(13.6)
1-year HV			2.49	(15.9)			2.94	(17.3)
1-month RV(C)			1.97	(19.7)			1.65	(16.0)
1-year JI			0.94	(10.4)			1.10	(11.6)
1-year JV			1.22	(8.1)			1.57	(10.7)
1-year JP			-0.67	(15.7)			-0.62	(14.7)
1-year JN			0.37	(8.3)			0.26	(6.1)
Rating (AAA)	33.48	(2.1)	-166.67	(11.6)	-71.34	(1.3)	-205.34	(4.4)
Rating (AA)	36.72	(4.7)	-146.40	(18.4)	-76.05	(1.4)	-184.05	(4.1)
Rating (A)	56.15	(16.0)	-132.42	(22.2)	-61.11	(1.1)	-177.01	(3.9)
Rating (BBB)	141.29	(50.4)	-68.60	(10.4)	12.74	(0.2)	-121.13	(2.7)
Rating (BB)	428.21	(73.7)	142.66	(16.1)	278.61	(5.1)	84.96	(1.9)
Rating (B)	745.31	(79.8)	349.20	(27.7)	544.38	(9.9)	239.69	(5.3)
Rating (CCC)	1019.60	(36.5)	552.25	(21.7)	503.92	(7.4)	98.61	(1.8)
S&P 500 return					-1.86	(7.5)	-1.23	(8.4)
S&P 500 vol					4.46	(3.9)	-3.03	(3.1)
Short rate					17.36	(2.9)	2.70	(0.5)
Term spread					26.23	(3.5)	16.13	(2.7)
Recovery rate					-2.59	(5.4)	0.12	(0.3)
ROE					-3.89	(12.5)	-0.91	(3.4)
Leverage ratio					0.53	(4.3)	0.70	(6.9)
Coverage ratio					-0.023	(2.1)	-0.002	(0.2)
Div. payout ratio					3.74	(0.9)	12.86	(3.6)
Adjusted R^2	0.57		0.73		0.63		0.75	
Obs.	6124		5784		4574		4366	

Table 6: **Robustness check: panel data estimation**

	Fixed Effect				**Random Effect**			
Regression	**1**		**2**		**1**		**2**	
	coef	*t-stat*	*coef*	*t-stat*	*coef*	*t-stat*	*coef*	*t-stat*
1-year Return			-0.73	(16.2)			-0.70	(15.7)
1-year HV	2.96	(16.4)	0.82	(4.4)	2.74	(19.2)	1.17	(6.5)
1-month RV(C)	2.61	(32.5)	1.67	(21.0)	2.56	(32.1)	1.69	(21.4)
1-year JI	0.10	(0.7)	0.10	(0.7)	-0.07	(0.5)	0.37	(2.8)
1-year JV	0.96	(0.7)	1.17	(8.4)	0.74	(4.9)	1.17	(8.4)
1-year JP	-0.71	(15.2)	-0.52	(11.8)	-0.68	(14.8)	-0.50	(11.6)
1-year JN	0.52	(9.8)	0.38	(7.9)	0.59	(11.6)	0.42	(9.1)
Rating (AAA)							-206.72	(4.4)
Rating (AA)			19.70	(0.5)			-189.42	(4.4)
Rating (A)			52.77	(1.6)			-149.84	(3.9)
Rating (BBB)			79.91	(2.4)			-105.95	(2.7)
Rating (BB)			109.01	(3.1)			-27.45	(0.7)
Rating (B)			148.79	(3.8)			52.08	(1.3)
Rating (CCC)							150.91	(1.5)
S&P 500 return			-1.12	(10.1)			-1.14	(10.4)
S&P 500 vol			-2.43	(3.1)			-1.98	(2.6)
Short rate			7.81	(2.0)			10.10	(2.6)
Term spread			18.34	(4.1)			19.80	(4.4)
Recovery rate			0.27	(0.7)			0.23	(0.6)
ROE			0.21	(0.8)			0.05	(0.2)
Leverage ratio			1.05	(3.7)			1.32	(5.4)
Coverage ratio			-0.02	(1.9)			-0.013	(1.2)
Div. payout ratio			36.52	(7.8)			33.84	(7.5)
Adjusted R^2	0.81		0.87		–		–	
Obs.	6064		4366		6064		4366	

Table 7: **Interactive effects of equity volatilities and jumps**

Regression	**1**		**2**	
	coef	*t-stat*	*coef*	*t-stat*
Constant	-64.88	(1.5)	49.55	(0.8)
1-year Return	-0.49	(10.3)	-0.56	(11.9)
HV*Group 1	2.28	(8.1)	12.29	(9.0)
HV*Group 2	2.64	(12.0)	12.81	(9.6)
HV*Group 3	4.69	(22.4)	14.44	(10.7)
RV(C)*Group 1	0.37	(2.1)	-11.86	(12.9)
RV(C)*Group 2	1.77	(12.2)	-10.37	(11.4)
RV(C)*Group 3	2.53	(14.3)	-9.60	(10.3)
JI*Group 1	1.19	(5.2)	2.31	(2.6)
JI*Group 3	2.70	(16.4)	4.26	(4.7)
JV*Group 1	0.58	(1.9)	2.92	(2.1)
JV*Group 3	3.92	(18.6)	5.90	(4.6)
JP*Group 1	-0.24	(2.3)	-1.87	(4.6)
JP*Group 2	-0.29	(4.6)	-1.84	(4.7)
JP*Group 3	-1.08	(16.1)	-2.43	(6.2)
S&P 500 return	-1.38	(9.7)	-1.39	(10.3)
S&P 500 vol	-2.91	(3.1)	-3.17	(3.6)
3M Treasury rate	4.86	(1.0)	-6.66	(1.4)
Term spread	8.43	(1.4)	8.59	(1.6)
Recovery rate	0.18	(0.5)	1.37	(1.3)
ROE	-0.91	(3.6)	-3.81	(5.5)
Leverage ratio	0.73	(7.4)	-2.03	(6.9)
Coverage ratio	-0.01	(0.5)	0.01	(0.5)
Div payout ratio	12.84	(3.7)	12.71	(1.1)
HV*Recovery			-29.16	(9.5)
HV*ROE			7.41	(5.0)
HV*Leverage			2.88	(3.4)
RV(C)*Recovery			27.42	(13.0)
RV(C)*ROE			-3.52	(2.6)
RV(C)*Leverage			2.31	(3.8)
RV(C)*DivPayout			36.01	(2.5)
JV*Recovery			-5.96	(2.0)
JP*Recovery			4.16	(4.6)
JP*ROE			2.73	(3.6)
JN*Leverage			1.32	(4.9)
Adjusted R^2	0.77		0.80	
Obs.	4366		4366	

Notes: " Group 1" is a dummy variable that incudes ratings AAA, AA ad A; "Group 2" is a dummy variable of rating BBB; and "Group 3" is a dummy variable that includes ratings BB, B and CCC. Interaction terms only includes those with t-ratios larger than 2.0 in the second regression.

Table 8: **Nonlinear effects of equity volatilities and jumps**

Regression	**1**		**2**	
	coef	*t-stat*	*coef*	*t-stat*
Constant	-28.35	(1.4)		
1-year Return	-0.25	(4.4)	-0.68	(14.1)
HV	-3.14	(2.4)	-5.34	(4.2)
HV^2	2.13	(6.6)	1.86	(5.4)
HV^3	-0.11	(4.6)	-0.11	(3.9)
RV(C)	0.25	(0.5)	0.18	(0.4)
$RV(C)^2$	0.37	(3.6)	0.26	(2.6)
$RV(C)^3$	-0.01	(2.8)	-0.01	(1.3)
JI	3.57	(6.1)	2.76	(5.9)
JI^2	-0.39	(3.9)	-0.44	(5.2)
JI^3	0.01	(2.6)	0.03	(5.1)
JV	2.18	(3.9)	0.36	(0.8)
JV^2	-0.40	(3.5)	0.26	(3.0)
JV^3	0.02	(4.3)	-0.01	(2.9)
JP	-0.67	(3.6)	-0.46	(3.0)
JP^2	-0.01	(0.7)	-0.01	(1.0)
JP^3	0.001	(1.8)	0.0003	(1.1)
JN	-0.41	(2.1)	-0.29	(2.0)
JN^2	0.09	(6.2)	0.06	(5.2)
JN^3	-0.002	(6.4)	-0.001	(5.1)
Rating (AAA)			-107.06	(2.3)
Rating (AA)			-91.44	(2.0)
Rating (A)			-79.11	(1.7)
Rating (BBB)			-19.78	(0.4)
Rating (BB)			184.36	(4.0)
Rating (B)			301.08	(6.5)
Rating (CCC)			254.63	(4.5)
S&P 500 return			-1.20	(8.4)
S&P 500 vol			-0.09	(0.1)
3M Treasury rate			14.35	(3.0)
Term spread			26.64	(4.6)
Recovery rate			-0.06	(0.2)
ROE			-1.20	(4.7)
Leverage ratio			0.71	(7.3)
Coverage ratio			-0.001	(0.1)
Div payout ratio			7.09	(2.1)
Adjusted R^2	0.57		0.78	
Obs.	6064		4366	

Table 9: **Monte Carlo evidence on the predictability of CDS spreads**

Variables	Merton (1974) Model						
1-year vol	1.14				0.59	1.18	1.10
	(1.54)				(1.15)	(0.48)	(1.60)
1-month vol		0.97			0.59		
		(1.56)			(1.52)		
1-year vol^2			6.19			1.08	
			(2.04)			(0.07)	
1-year vol×value				-0.41			-0.35
				(1.19)			(1.65)
R-Square	0.53	0.57	0.53	0.25	0.65	0.56	0.75
	(2.37)	(2.73)	(2.39)	(1.54)	(3.45)	(2.48)	(4.55)
Variables	Stochastic Volatility Model						
1-year vol	5.78				4.77	4.74	5.71
	(1.91)				(1.69)	(0.15)	(2.06)
1-month vol		2.96			1.09		
		(1.65)			(1.62)		
1-year vol^2			66.76			26.86	
			(2.31)			(0.07)	
1-year vol×value				-1.02			-0.95
				(1.51)			(1.91)
R-Square	0.51	0.34	0.51	0.25	0.55	0.55	0.72
	(2.19)	(1.93)	(2.16)	(1.51)	(2.52)	(2.36)	(4.24)

Notes: Monte Carlo t-ratios are reported in the parentheses.

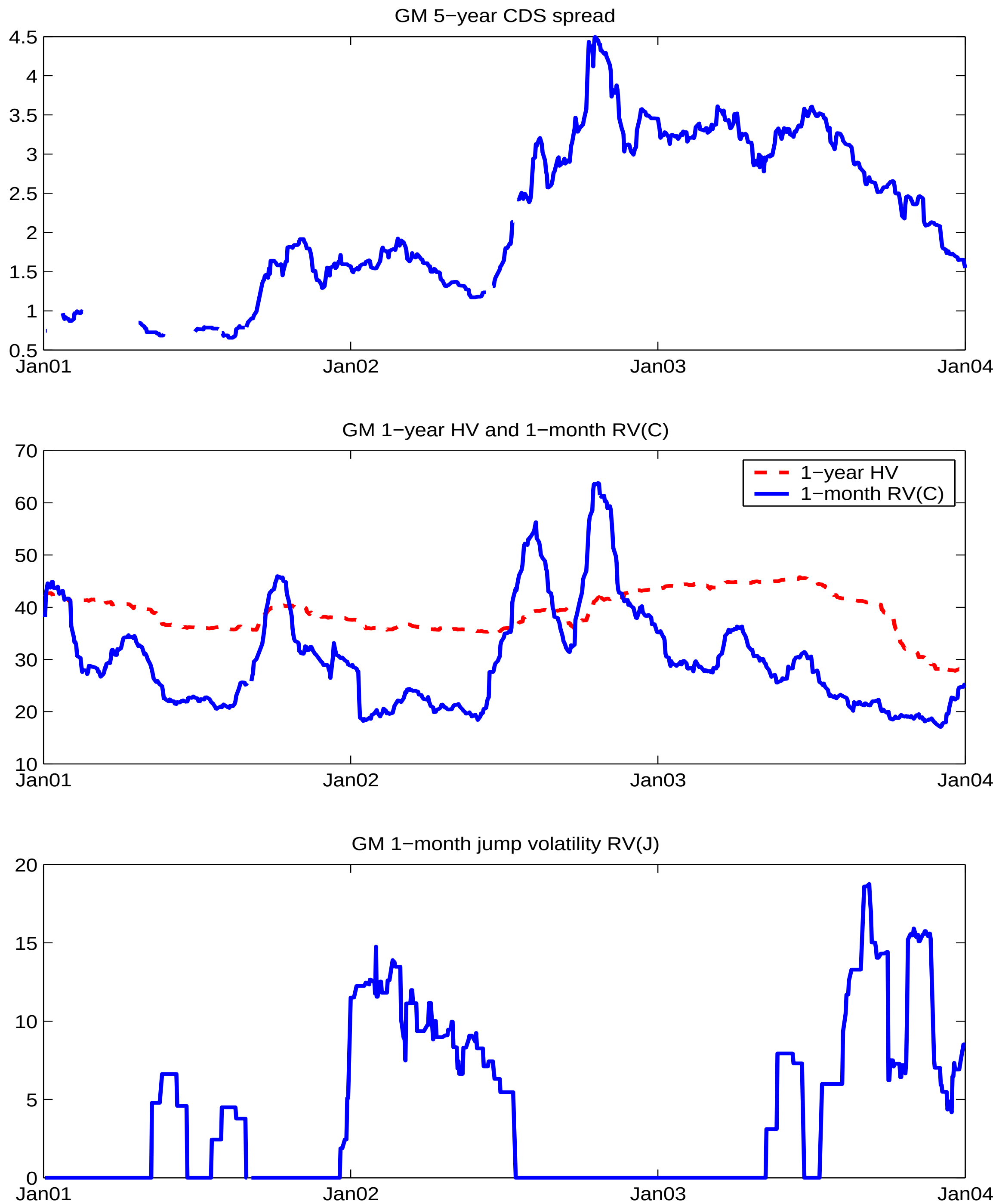

Figure 1: An example - General Motors

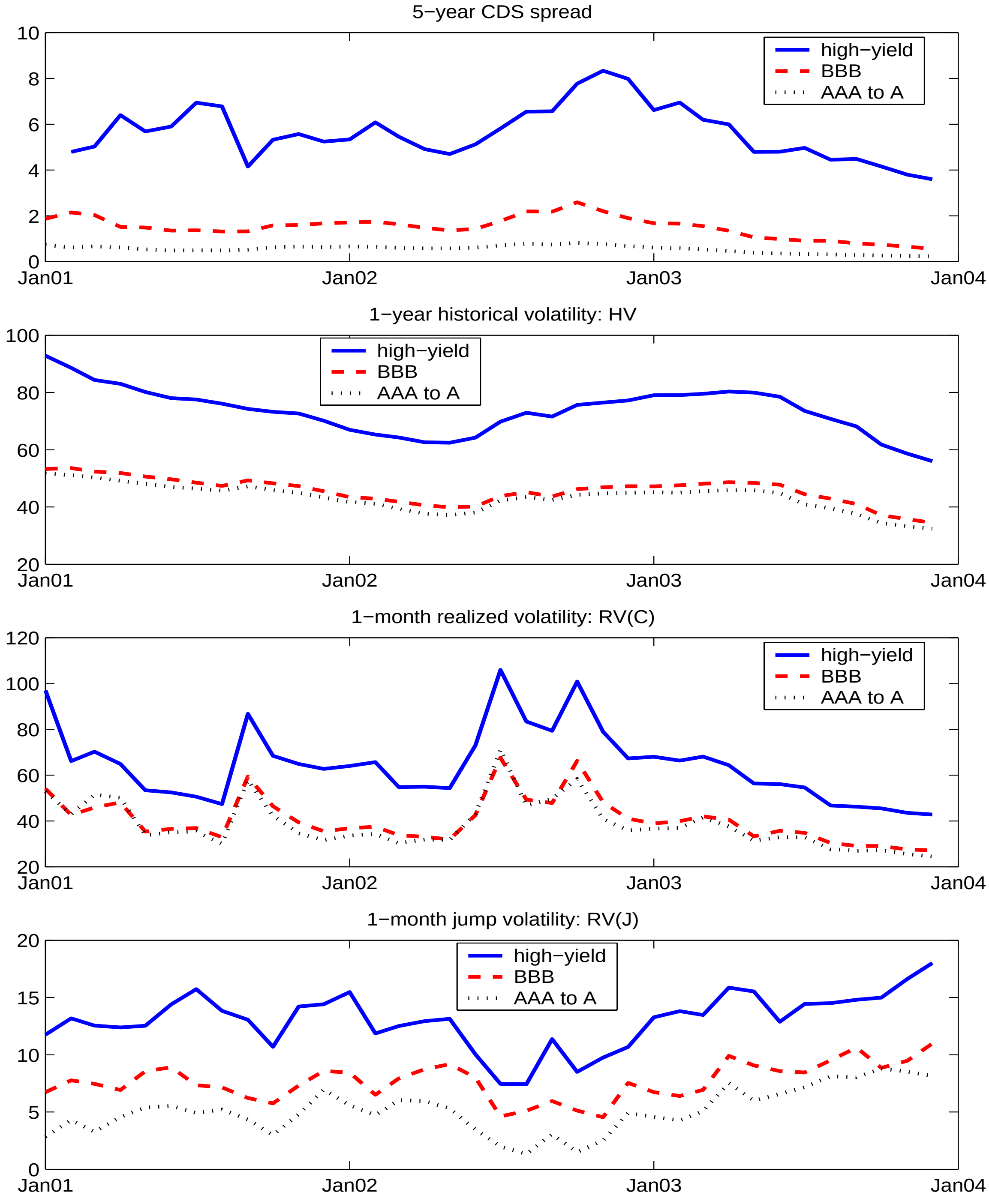

Figure 2: CDS spreads and volatility risks by rating groups

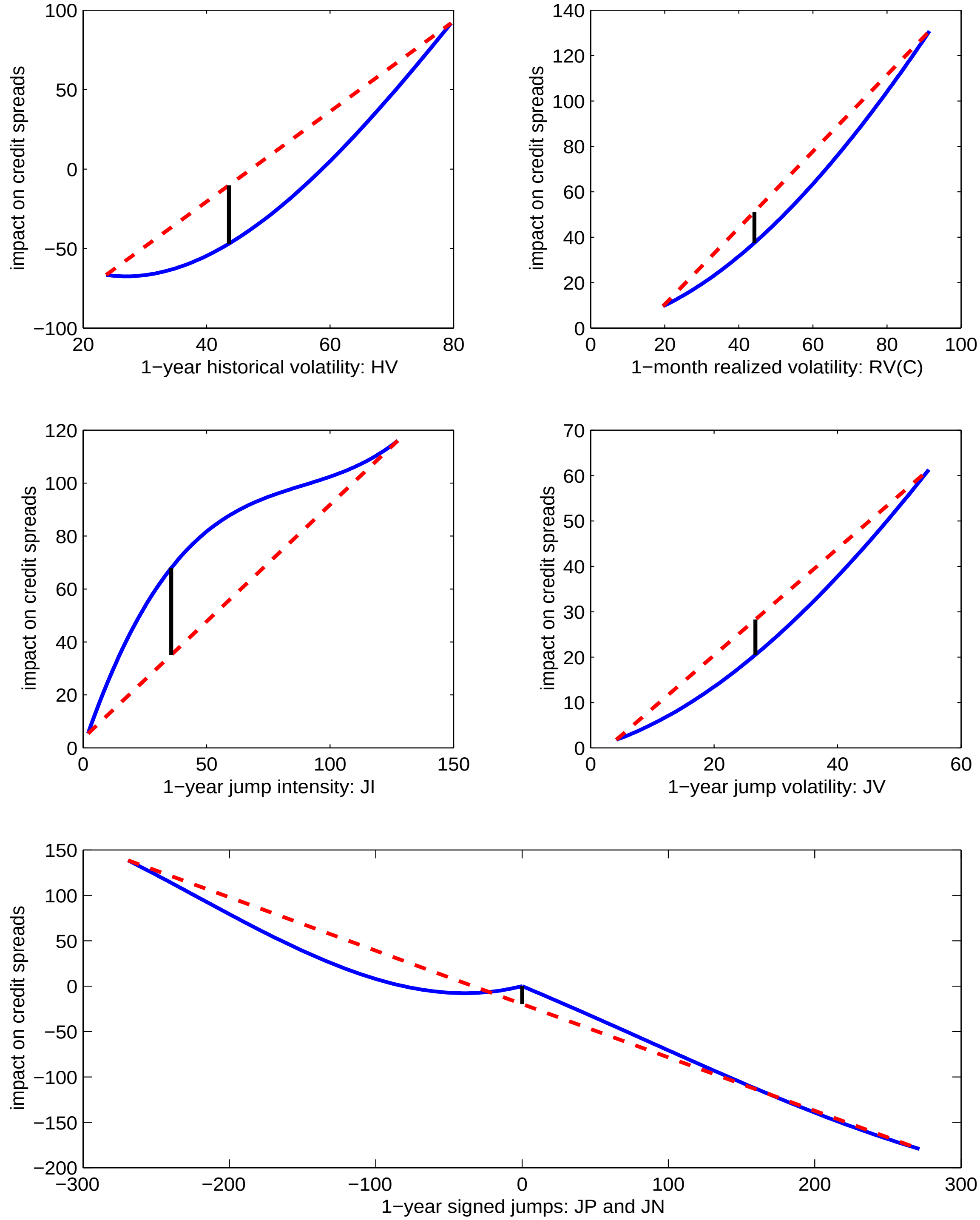

Figure 3: Nonlinear effect of individual volatility

Note: The illustration is based on regression 1 in Table 8. X-axis variables have the value range of 5% and 95% percentiles, with the vertical line corresponding to their mean.

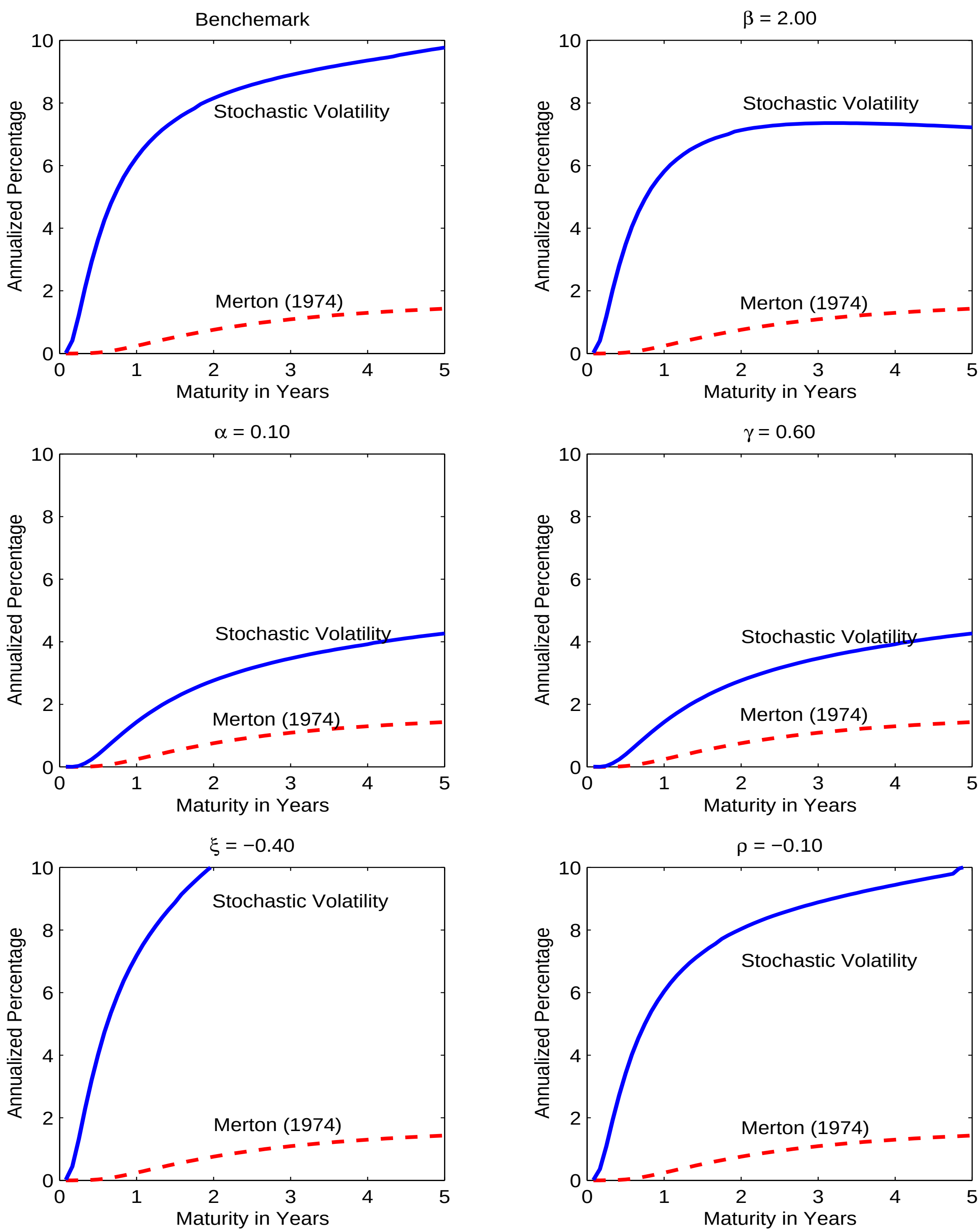

Figure 4: Simulated term structure of credit spread

Note: The benchmark parameter setting is $\beta = 0.10$, $\alpha = 0.25$, $\gamma = 0.10$, $\xi = -0.20$, and $\rho = -0.50$.