BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers

No 181

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

by Benjamin Yibin Zhang, Hao Zhou & Haibin Zhu

Monetary and Economic Department

September 2005

JEL Classification Numbers: G12, G13, C14
Keywords: Structural Model; Stochastic Volatility; Jumps; Credit Spread; Credit Default Swap; Nonlinear Effect; High Frequency Data

Copies of publications are available from:

Bank for International Settlements
Press & Communications
CH-4002 Basel, Switzerland

E-mail: publications@bis.org

Fax: +41 61 280 9100 and +41 61 280 8100

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)

ISSN 1682-7678 (online)

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: September 2005

Abstract

A structural model with stochastic volatility and jumps implies particular relationships between observed equity returns and credit spreads. This paper explores such effects 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 volatility risk alone predicts 50% of CDS spread variation, while jump risk alone forecasts 19%. After controlling for credit ratings, macroeconomic conditions, and firms' balance sheet information, we can explain 77% of the total variation. Moreover, the marginal impacts of volatility and jump measures increase dramatically from investment grade to high-yield entities. The estimated nonlinear effects of volatility and jumps are in line with the model implied-relationships between equity returns and credit spreads.

JEL Classification Numbers: G12, G13, C14.
Keywords: Structural Model; Stochastic Volatility; Jumps; Credit Spread; Credit Default Swap; Nonlinear Effect; High Frequency Data.

*The views presented here are solely those of the authors and do not necessarily represent those of Fitch Ratings, the Federal Reserve Board, or the Bank for International Settlements. We thank Jeffrey Amato, Ren-Raw Chen, Greg Duffee, Mike Gibson, Jean Helwege, Jingzhi Huang, and George Tauchen for detailed discussions. Comments from seminar participants at the Federal Reserve Board, the 2005 FDIC Derivative Conference, the Bank for International Settlements, and the 2005 Pacific Basin Conference at Rutgers are greatly appreciated.

†Benjamin Yibin Zhang, Fitch Ratings, One State Street Plaza, New York, NY 10004, USA. Tel.: 1-212-908-0201. Fax: 1-914-613-0948. E-mail: ben.zhang@fitchratings.com.

‡Hao Zhou, Federal Reserve Board, Mail Stop 91, Washington, DC 20551, USA. Tel.: 1-202-452-3360. Fax: 1-202-728-5887. E-mail: hao.zhou@frb.gov.

§Haibin Zhu, Bank for International Settlements, Centralbahnplatz 2, 4002 Basel, Switzerland. Tel.: 41-61-280-9164. Fax: 41-61-280-9100. E-mail: haibin.zhu@bis.org.

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

Abstract

A structural model with stochastic volatility and jumps implies particular relationships between observed equity returns and credit spreads. This paper explores such effects 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 volatility risk alone predicts 50% of CDS spread variation, while jump risk alone forecasts 19%. After controlling for credit ratings, macroeconomic conditions, and firms' balance sheet information, we can explain 77% of the total variation. Moreover, the marginal impacts of volatility and jump measures increase dramatically from investment grade to high-yield entities. The estimated nonlinear effects of volatility and jumps are in line with the model-implied relationships between equity returns and credit spreads.

JEL Classification Numbers: G12, G13, C14.

Keywords: Structural Model; Stochastic Volatility; Jumps; Credit Spread; Credit Default Swap; Nonlinear Effect; High Frequency Data.

1 Introduction

The empirical tests for structural models of credit risk have been unsuccessful. Strict estimation or calibration reveals that the predicted credit spread is far below observed credit spreads (Jones et al., 1984), the structural variables explain very little of the credit spread variation (Huang and Huang, 2003), and pricing error is very large for corporate bonds (Eom et al., 2004). More flexible regression analysis, while it confirms the validity of the cross-sectional or long-run factors in predicting the bond spread, suggests that the explaining power of default risk factors for credit spread is still very small (Collin-Dufresne et al., 2001), the temporal changes of bond spread are not directly related to expected default loss (Elton et al., 2001), or the forecasting power of long-run volatility cannot be reconciled with the classical Merton (1974) model (Campbell and Taksler, 2003). These negative findings are robust to the extensions of stochastic interest rates (Longstaff and Schwartz, 1995), endogenously determined default boundaries (Leland, 1994; Leland and Toft, 1996), strategic defaults (Anderson et al., 1996; Mella-Barral and Perraudin, 1997), and mean-reverting leverage ratios (Collin-Dufresne and Goldstein, 2001).

We argue that incorporating stochastic volatility and jumps in the asset value process (Huang, 2005) may enable structural variables to adequately explain credit spread variations, especially in the time series dimension. The most important finding in Campbell and Taksler (2003) is that the recent increases in corporate yields can be explained by the upward trend in idiosyncratic equity volatility, but the magnitude of volatility coefficient is clearly inconsistent with the structural model of constant volatility (Merton, 1974). Nevertheless, incorporating jumps in theory should better explain the level of credit spreads for investment grade bonds at short maturities (Zhou, 2001), but the empirical evidence is rather mixed. Collin-Dufresne et al. (2001, 2003) use a market-based jump risk measure and find that it explains only a very small proportion of credit spread. Cremers et al. (2004a,b) instead rely on individual option-implied skewness and find some positive evidence. We demonstrate numerically that adding stochastic volatility and jumps into the classical Merton (1974) model can dramatically increase the flexibility of the entire credit curve, with the potential to better match observed yield spreads and to better forecast temporal variation. In particular, we outline the testable empirical hypotheses between the observable equity returns and credit spreads implied by the underlying asset return process. This is important, since asset value and volatility are generally not observed and the testing of structural models has to rely heavily on observed equity return and volatility.

We adopt both historical and realized measures to proxy for the time variation in equity volatility, and several jump measures to proxy for the various aspects of the jump risk. Our key innovation is to use the high frequency equity returns of individual firms to detect the realized jumps on each day. Recent literature suggests that realized variance measures from high frequency data provide a more accurate measure of short-term volatility (Andersen et al., 2001; Barndorff-Nielsen and Shephard, 2002; Meddahi, 2002). Furthermore, the continuous and jump contributions can be separated by comparing the difference between bipower variation and quadratic variation (Barndorff-Nielsen and Shephard, 2004; Andersen et al., 2004; Huang and Tauchen, 2005). 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 dominates daily return when it occurs, which helps us to identify daily realized jumps of equity returns (Tauchen and Zhou, 2005). We can further estimate the jump intensity, jump mean, and jump volatility from these realized jumps, and directly test the implications between equity returns and credit spread implied by the structural model mentioned above with stochastic volatility and jumps in the asset value process.

In this paper we rely on the credit default swap (CDS) premium, the most popular instrument in the rapidly growing credit derivatives markets, as a direct measure of credit default spreads. Compared with corporate bond spreads, which were widely used in previous studies in testing structural models, CDS spreads have two important 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 arrangements, such as seniority, coupon rates, embedded options, and guarantees. For example, Longstaff et al. (2005) find that a large proportion of bond spreads are determined by liquidity factors, which do not necessarily reflect the default risk of the underlying asset. Second, Blanco et al. (2005) and Zhu (2004) show that, while CDS and bond spreads are quite in line with each other in the long run, in the short run CDS spreads tend to respond more quickly to changes in credit conditions. This could be partly attributed to the fact that CDSs are unfunded and do not face short-sale restrictions. The fact that CDSs lead the bond market in price discovery is instrumental for our improved explanation of the temporal changes in credit spread by default risk factors.

In contrast to the common empirical strategy that simultaneously regresses credit spreads on structural variables constructed from equity data, we only use the lagged explanatory variables. Under a typical structural framework, only asset return and volatility are exogenous processes, while equity return and volatility as well as credit spread are all endogenously determined. Simultaneous regressions without structural restrictions would artificially inflate the R-squares and t-statistics. Our empirical findings suggest that long-run historical volatility, short-run realized volatility, and various jump risk measures all have statistically significant and economically meaningful impacts on credit spreads. Realized jump measures explain 19% 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 54% of the spread variations. After controlling for credit ratings, macro-financial variables, and firms' accounting information, the signs and significance of jump and volatility impacts remain solid, and the R-square increases to 77%. These results are robust to whether the fixed effect or the random effect is taken into account, suggesting that the temporal variation of default risk factors does explain the CDS spreads. More importantly, the sensitivity of credit spreads to volatility and jump risk is greatly elevated from investment grade to high-yield entities, which has implications for managing more risky credit portfolios. Last but not least, both volatility and jump risk measures show strong nonlinear effects, which is consistent with the hypotheses implied by the structural model with stochastic volatility and jumps.

The remainder of the paper is organized as follows. Section 2 introduces the structural link between equity and credit and discusses the methodology for disentangling volatility and jumps using high frequency data. Section 3 gives a brief description of 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. Section 5 concludes.

2 Structural motivation and econometric technique

Testing structural models of credit risk is difficult because the underlying asset value and its volatility processes are not observable; therefore, approximations from observed equity price and volatility have been a common practice. However, many listed firms have their equity shares and credit derivatives traded on relatively liquid markets, therefore researchers are prompted to directly model the observable equity dynamics to explain and predict the credit spreads (Madan and Unal, 2000; Das and Sundaram, 2004; Carr and Wu, 2005). Nevertheless, structural models can still provide important economic intuitions on how to interpret the empirical linkage between equity and credit. Here we motivate our empirical exercise by examining the model-implied equity-credit relationship from an affine structural model.

2.1 A stylized model with stochastic volatility and jumps

Assuming the same market environment as in Merton (1974), one can introduce stochastic volatility (Heston, 1993) and jumps (Zhou, 2001) in the underlying firm value process,

$$\frac{dA_t}{A_t} = (\mu - \delta - \lambda\mu_J)dt + \sqrt{V_t}dW_{1t} + J_t dq_t \tag{1}$$

$$dV_t = \kappa(\theta - V_t)dt + \sigma\sqrt{V_t}dW_{2t} \tag{2}$$

where A_t is the firm value, μ is the instantaneous asset return, and δ is the dividend payout ratio. Asset jump has a Poisson mixing Gaussian distribution with $dq_t \sim$ Poisson (λdt) and $\log(1 + J_t) \sim$ Normal $(\log(1 + \mu_J) - \frac{1}{2}\sigma_J^2,\ \sigma_J^2)$. The asset return volatility V_t follows a square root process with long-run mean θ, mean reversion κ, and variance parameter σ. Finally, the correlation between asset return and return volatility is corr $(dW_{1t}, dW_{2t}) = \rho$.

Such a specification has been extensively studied in the option pricing literature (see Bates, 1996; Bakshi et al., 1997, for example), and is suitable for pricing corporate debt (Huang, 2005).[1] Assuming no-arbitrage, the risk-neutral dynamics is

$$\frac{dA_t}{A_t} = (r - \delta - \lambda^*\mu_J^*)dt + \sqrt{V_t}dW_{1t}^* + J_t^* dq_t^* \tag{3}$$

$$dV_t = \kappa^*(\theta^* - V_t)dt + \sigma\sqrt{V_t}dW_{2t}^* \tag{4}$$

where r is the risk-free rate, $\log(1 + J_t^*) \sim$ Normal $(\log(1 + \mu_J^*) - \frac{1}{2}\sigma_J^2,\ \sigma_J^2)$, $dq_t^* \sim$ Poisson $(\lambda^* dt)$, and corr $(dW_{1t}^*, dW_{2t}^*) = \rho$. The volatility risk premium is ξ_v such that $\kappa^* = \kappa + \xi_v$ and $\theta^* = \theta\xi_v/\kappa^*$, the jump intensity risk premium is ξ_λ such that $\lambda^* = \lambda + \xi_\lambda$, and the jump size risk premium is ξ_J such that $\mu_J^* = \mu_J + \xi_J$.

[1] The required assumptions are that default occurs only at maturity with fixed default boundary and that when default occurs there is no bankruptcy cost and the absolute priority rule is adopted (Huang, 2005).

Equity price S_t can be solved as a European call option on debt D_t with face value B and maturity time T, using the solution method of Duffie et al. (2000)

$$S_t = A_t F_1^* - Be^{-r(T-t)} F_2^* \tag{5}$$

where F_1^* and F_2^* are risk-neutral probabilities. Therefore the debt value can be expressed as $D_t = A_t - S_t$, and its price is $P_t = D_t/B$. The credit default spread is then given by

$$R_t - r = -\frac{1}{T-t} \log(P_t) - r \tag{6}$$

2.2 The sensitivity of credit spread to asset volatility and jumps

Figure 1 plots the credit yield curves from both the Merton (1974) model and the jump diffusion stochastic volatility (JDSV) model, with the same asset return volatilities that match the high-yield entities (Longstaff and Schwartz, 1995).[2] The 5-year credit spread of the JDSV model is 479 basis points, matching the high-yield credit spread observed in our sample, while the 5-year credit spread of Merton's model is 144 basis points, close to investment grade. This difference highlights the finding that Merton's model typically underfits the observed bond spread (Jones et al., 1984), while introducing time-varying volatility here clearly produces higher credit spread. Incorporating jumps allows the short end (1 month) of the yield curve to be significantly higher than zero (13 basis points).

The sensitivities of credit curves with respect to volatility and jump parameters have an intuitive pattern. As shown in Figure 2, the high volatility state $V_t^{1/2}$ increases credit spread very dramatically at shorter maturities less than one year, and the credit curve becomes inverted when the volatility level is high (50%). High mean reversion of volatility κ reduces spread (less persistent), while high long-run mean of volatility θ increases spread (more risky). However, the volatility-of-volatility σ and volatility-asset correlation ρ have rather muted effects on spread, and the impact signs are not uniform across all maturities. Finally, the jump mean μ_J seems to have non-monotonic and asymmetric effects on credit spread, i.e., both positive and negative jump means will elevate the credit spread, but

[2] The parameter values are chosen as $r = 0.05$, $T - t = 5$, $K/A = 0.6$, $\mu = 0$, $\delta = 0$; $V_t = 0.09$, $\kappa = 2$, $\theta = 0.09$, $\sigma = 0.4$, $\rho = -0.6$; $\lambda = 0.05$, $\mu_J = 0$, $\sigma_J = 0.4$; $\xi_v = -1.2$, $\xi_\lambda = 0$, $\xi_J = 0$. Such a setting is similar to several scenarios examined in Longstaff and Schwartz (1995) and Zhou (2001), therefore we only report the comparative statics that are different from the previous studies. The unconditional asset volatility $\sqrt{\theta + \lambda \sigma_J^2} = 0.313$ is the same across both JDSV and Merton (1974) models. The values of κ, σ, and ρ are adapted from Bakshi et al. (1997).

negative jump means seem to raise spread higher.[3]

2.3 Testable hypotheses between equity and credit

The stochastic volatility jump diffusion model (1-6) of asset value and volatility processes implies the following specification of equity price, by applying the Itô Lemma,

$$\begin{aligned}\frac{dS_t}{S_t} &= \frac{1}{S_t}\mu_t(\cdot)dt + \frac{A_t}{S_t}\frac{\partial S_t}{\partial A_t}\sqrt{V_t}dW_{1t} + \frac{1}{S_t}\frac{\partial S_t}{\partial V_t}\sigma\sqrt{V_t}dW_{2t} \\ &\quad + \frac{1}{S_t}[S_t(A_t(1+J_t), V_t;\Omega) - S_t(A_t, V_t;\Omega)]dq_t \qquad (7)\end{aligned}$$

where $\mu_t(\cdot)$ is the instantaneous equity return, Ω is the parameter vector, A_t and V_t are the latent asset and volatility processes, and $S_t \equiv S_t(A_t, V_t; \Omega)$. Therefore the instantaneous volatility Σ_t^s and jump size J_t^s of the log equity price are, respectively,

$$\Sigma_t^s = \sqrt{\left(\frac{A_t}{S_t}\right)^2\left(\frac{\partial S_t}{\partial A_t}\right)^2 V_t + \left(\frac{\sigma}{S_t}\right)^2\left(\frac{\partial S_t}{\partial V_t}\right)^2 V_t + \frac{A_t}{S_t^2}\frac{\partial S_t}{\partial A_t}\frac{\partial S_t}{\partial V_t}\rho\sigma V_t} \qquad (8)$$

$$J_t^s = \log[S_t(A_t(1+J_t), V_t;\Omega)] - \log[S_t(A_t, V_t;\Omega)] \qquad (9)$$

where J_t^s has unconditional mean μ_J^s and standard deviation σ_J^s, which are not known in closed form, due to the nonlinear functional form of $S_t(A_t, V_t; \Omega)$. Obviously the equity volatility is driven by the two time-varying factors A_t and V_t, while the asset volatility is simply driven by V_t. However, if asset volatility is constant (V), then equation (8) reduces to the standard Merton (1974) formula, $\Sigma_t^s = \sqrt{V}\frac{\partial S_t}{\partial A_t}\frac{A_t}{S_t}$. The Poisson driving process of equity jump is the same as asset jump, hence the same intensity function $\lambda^s = \lambda$.

The most important empirical implication is how *credit* spread responds to changes in *equity* jump and volatility parameters, implied by the underlying changes in *asset* jump and volatility parameters, as illustrated numerically in Figure 3. The left column suggests that 5-year credit spread would increase linearly with the levels of asset volatility ($V_t^{1/2}$) and jump intensity (λ). Asset jump volatility (σ_J) would also raise credit spread, but in a nonlinear convex fashion. Interestingly, the asset jump mean (μ_J) increases credit spread when moving away from zero.

[3]Since the risk premium parameters ξ_v, ξ_λ, and ξ_J enter the pricing equation additively with κ, λ, and μ_J, their impacts on credit spreads are also the same as those parameters and hence omitted. In addition, the positive impacts of jump intensity λ and jump volatility on σ_J on credit spread are similar to Zhou (2001) and are hence omitted.

More interestingly, the impact is nonlinear and asymmetric—the negative jump mean increases spread much more than the positive jump mean. This is because the first order effect of jump mean changes may be offset by the drift compensator, and the second order effect is equivalent to jump volatility increases, due to the log-normal jump distribution.

Given the same changes in structural asset volatility and jump parameters, the right column plots credit spread changes as related to the *equity* jump and volatility parameters. Clearly, equity volatility (Σ_t^s) still increases credit spread, but in a nonlinear convex pattern. Note that equity volatility is about three times as large as asset volatility, mostly due to the leverage effect. Equity jump intensity (λ^s) is the same as asset jump intensity, so the linear effect on credit spread is also the same. Equity jump volatility (σ_J^s) has a similar positive nonlinear impact on credit spread, but the range of equity jump volatility is nearly twice as large as the asset jump volatility. Equity jump mean (μ_J^s) also has a nonlinear asymmetric impact on credit spread, with the equity jump mean being more negative than the asset jump mean.[4] Of course, in a linear regression setting, one would only find the approximate negative relationship between equity jump mean and credit spread. These relationships, illustrated in Figure 3, are qualitatively robust to various values of the structural parameters.

To summarize, the following empirical hypotheses may be tested between equity price and credit spread:

H1: Equity volatility increases credit spread nonlinearly through two factors;

H2: Equity jump intensity increases credit spread linearly;

H3: Equity jump mean affects credit spread in a nonlinear asymmetric way; negative jumps tend to have large impacts;

H4: Equity jump volatility nonlinearly increases credit spread.

2.4 Disentangling jump and volatility risks of equities

In this paper, we rely on the economic intuition that jumps on financial markets are rare and of large size, to explicitly estimate the jump intensity, jump variance, and jump mean, and to directly assess the empirical impacts of volatility and jump risks on credit spreads.

Let $s_t \equiv \log S_t$ denote the time t logarithmic price of the stock, which evolves

[4] Equity jump mean μ_J^s and standard deviation σ_J^s do not admit closed form solutions. So at each grid of structural parameter values of μ_J and σ_J, we simulate asset jump 2000 times and numerically evaluate μ_J^s and σ_J^s.

in continuous time as a jump diffusion process:

$$ds_t = \mu_t^s dt + \sigma_t^s dW_t + J_t^s dq_t \tag{10}$$

where μ_t^s, σ_t^s, and J_t^s are, respectively, the drift, diffusion, and jump functions that may be more general than the model-implied equity process (7). W_t is a standard Brownian motion (or a vector of Brownian motions), dq_t is a Poisson driving process with intensity $\lambda^s = \lambda$, and J_t^s refers to the size of the corresponding log equity jump, which is assumed to have mean μ_J^s and standard deviation σ_J^s. Time is measured in daily units, and the daily return r_t is defined as $r_t^s \equiv s_t - s_{t-1}$. Historical volatility, defined as the standard deviation of daily returns, has been considered as a proxy for the volatility risk of the underlying asset value process (see, e.g., Campbell and Taksler, 2003). The intra-day returns are defined as follows:

$$r_{t,i}^s \equiv s_{t,i\cdot\Delta} - s_{t,(i-1)\cdot\Delta} \tag{11}$$

where $r_{t,i}$ refers to the i^{th} within-day return on day t, and Δ is the sampling frequency.[5]

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

$$\mathrm{RV}_t \equiv \sum_{i=1}^{1/\Delta} (r_{t,i}^s)^2 \to \int_{t-1}^{t} \sigma_s^2 ds + \sum_{i=1}^{1/\Delta} (J_{t,i}^s)^2 \tag{12}$$

$$\mathrm{BV}_t \equiv \frac{\pi}{2} \sum_{i=2}^{1/\Delta} |r_{t,i}^s| \cdot |r_{t,i-1}^s| \to \int_{t-1}^{t} \sigma_s^2 ds \tag{13}$$

Therefore the asymptotic difference between realized variance 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

[5] 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 noise (Aït-Sahalia et al., 2005; Bandi and Russell, 2005).

(2005). Here we adopt the ratio test statistics,

$$\mathrm{RJ}_t \equiv \frac{\mathrm{RV}_t - \mathrm{BV}_t}{\mathrm{RV}_t} \tag{14}$$

When appropriately scaled by its asymptotic variance, $z = \frac{\mathrm{RJ}_t}{\mathrm{Avar}(\mathrm{RJ}_t)}$ converges to a standard normal distribution.[6] This test tells us whether a jump occurred during a particular day, and how much jump(s) contributes to the total realized variance, i.e., the ratio of $\sum_{i=1}^{1/\Delta}(J_{t,i}^s)^2$ over RV_t.

To identify the actual jump sizes, we further assume that (1) there is at most one jump per day and (2) jump size dominates return on jump days. Following the idea of "significant jumps" in Andersen et al. (2004), we use the signed square root of significant jump variance to filter out the daily realized jumps,

$$J_t^s = \mathrm{sign}(r_t^s) \times \sqrt{\mathrm{RV}_t - \mathrm{BV}_t} \times \mathrm{I}(z > \Phi_\alpha^{-1}) \tag{15}$$

where Φ is the probability of a standard normal distribution and α is the level of significance chosen as 0.999. The filtered realized jumps enable us to estimate the jump distribution parameters directly,

$$\hat{\lambda}^s = \frac{\text{Number of Jump Days}}{\text{Number of Trading Days}} \tag{16}$$

$$\hat{\mu}_J^s = \text{Mean of } J_t^s \tag{17}$$

$$\hat{\sigma}_J^s = \text{Standard Deviation of } J_t^s \tag{18}$$

Tauchen and Zhou (2005) show that under empirically realistic settings, such a method of identifying realized jumps and estimating jump parameters yields reliable results in finite samples, as both the sample size increases and the sampling interval shrinks. We can also estimate the time-varying jump parameters for a rolling window (e.g., 1-year horizon $\hat{\lambda}_t^s$, $\hat{\mu}_{J,t}^s$, and $\hat{\sigma}_{J,t}^s$). Equipped with this technique, we are ready to re-examine the impact of jumps on credit spreads.

3 Data

Throughout this paper we choose to use the credit default swap (CDS) premium as a direct measure of credit spreads. CDS is the most popular instrument in the rapidly growing credit derivatives markets. Under a CDS contract the protection

[6] See Appendix A for implementation details. Similar to Huang and Tauchen (2005), we find that using the test level of 0.999 produces the most consistent results. We also use staggered returns in constructing the test statistics, to control for the potential measurement error problem.

seller promises to buy the reference bond at its par value when a pre-defined default event occurs. In return, the protection buyer makes periodic payments to the seller until the maturity date of the 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. By definition, credit spread provides a pure measure of the default risk of the reference entity.[7]

Our 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 on a daily basis. Based on the contributed quotes Markit creates the daily composite quote for each CDS contract.[8] Together with the pricing information, the dataset also reports average recovery rates used by data contributors in pricing each CDS 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) clauses[9] as they are the most popularly traded in the US 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. This much larger pool of constituent entities relative to previous studies makes us more comfortable in interpreting our empirical results.

Our sample coverage starts at January 2001 and ends at 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.[10] To avoid measurement errors we remove

[7]There has been a growing interest in examining the pricing determinants of credit derivatives 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).

[8]Three major filtering criteria are adopted to remove potential measurement errors: (1) an outlier criterion that removes quotes that are far above or below the average prices reported by other contributors; (2) a staleness criterion that removes contributed quotes that do not change for a very long period; and (3) a term structure criterion that removes flat curves from the dataset.

[9]Packer and Zhu (2005) examine different types of restructuring clauses traded in the market and their pricing implications. A modified restructuring contract has more restrictions on deliverable assets upon bankruptcy than the traditional full restructuring contract, and therefore should be related to a lower spread. Typically the price difference is less than 5%.

[10]Although composite quotes are available on a daily basis, we choose a monthly data frequency for two major reasons. First, balance sheet information is available only on a quarterly basis. Using daily data is very likely to understate the impact of firms' balance sheets on CDS pricing. Second, as most CDS contracts are not frequently traded, the CDS data suffer significantly from

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 they are often associated with absence of trading or a bilateral arrangement of an upfront payment.

Our explanatory variables include our measures of individual equity volatilities and jumps, rating information, and other standard structural factors including firm-specific balance sheet information and macro-financial variables. Appendix B describes the definitions and sources of those variables, and theoretical predictions of their impact on credit spreads are listed in Table 1.

To be more specific, we use two sets of measures for the equity volatility of individual firms as defined in Section 2.4: historical volatility calculated from daily equity prices and realized volatility calculated from intra-day equity prices. We calculate the two volatility measures over different time horizons (1-month, 3-month, and 1-year) to proxy for the time variation in equity volatility. We also define jumps on each day based on the ratio test statistics (equation (14)) with the significance level of 99.9% (see Appendix A for implementation details). After identifying daily jumps, we then calculate the average jump intensity, jump mean, and jump standard deviation in a month, a quarter, and a year.

Following the prevalent practice in the existing literature, our firm-specific variables include the firm leverage ratio, return on equity (ROE), and dividend payout ratio. And to proxy for the overall state of the economy, we use four macro-financial variables: the S&P 500 average daily return and its volatility in the past 6 months, and the average 3-month Treasury rate and the slope of the yield curve in the previous month.

4 Empirical evidence

In this section we first briefly describe the attributes of our volatility and jump measures, then mainly examine their role in explaining CDS spread movements.

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 dataset, so the standard ordinary least squares (OLS) regression is a suitable tool in our empirical analysis.

The benchmark regression is an OLS test that pools together all valid observations:

$$\begin{aligned}\text{CDS}_{i,t} &= c + b_v \cdot \text{Volatilities}_{i,t-1} + b_j \cdot \text{Jumps}_{i,t-1} \\ &\quad + b_r \cdot \text{Ratings}_{i,t-1} + b_m \cdot \text{Macro}_{i,t-1} + b_f \cdot \text{Firm}_{i,t-1} + \epsilon_{i,t}\end{aligned} \tag{19}$$

where the explanatory variables are vectors listed in Section 3 and detailed in Appendix B.

Note that we only use lagged explanatory variables, mainly to avoid the simultaneity problem. From a theoretical perspective, most explanatory variables, such as equity return and volatility, ratings, or option-implied volatility and skewness as used in Cremers et al. (2004a,b), are jointly determined with credit spreads. Therefore, the explanatory power might be artificially inflated by using simultaneous explanatory variables. In particular, it might generate biased results on the economic relevance of structural factors in explaining credit spreads, as the regression also tests for the consistency of prices in different markets (CDS, equity, and option markets).

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. The robustness check using a panel data technique does not alter our results qualitatively. In addition, we also test whether the influence of structural factors is related to the firms' financial condition by dividing the sample into three major rating groups. Our final exercise tests for the nonlinearity of the volatility and jump effect, as predicted by the model in Section 2.

4.1 Summary statistics

Table 2 reports the sectoral and rating distributions of our sample companies, and summary statistics of firm-specific accounting and macro-financial variables. Our sample entities 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.

CDS spreads exhibit substantial cross-sectional differences and time variations with a sample mean of 172 basis points. By rating categories, the average CDS spread for single-A to triple-A entities is 45 basis points, whereas the average spreads for triple-B and high-yield names are 116 and 450 basis points, respectively. In general, CDS spreads increased substantially in mid-2002, then gradually declined throughout the remaining sample period, as shown in Figure 4.

The summary statistics of firm-level volatilities and jump measures are reported in Table 3.[11] The average daily return volatility (annualized) is between 40-50%, independent of whether historical or realized measures are used. The two volatility measures are also highly correlated (the correlation coefficient is around 0.9). Concerning the jump measures, we detect significant jumps in about 16% of the transaction days. In those days when significant jumps have been detected, the jump component contributes to 52.3% of the total realized variance on average (the range is around 40-80% across the 307 entities). The infrequent occurrence and relative importance of the jump component validate the two assumptions we have used in the identification process.

Like CDS spreads, our volatility and jump measures also exhibit significant variation over time and across rating groups (Table 3 and Figure 4). High-yield entities are associated with higher equity volatility, but the distinction within the investment grade categories is less obvious. As for jump measures, lower-rated entities tend to be linked with lower jump volatility and smaller jump magnitude.

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 to proxy for the jump risk in previous studies.[12] On careful examination, this may reflect the inadequacy of both variables in measuring jumps. Historical skewness is an indicator of 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 indicator of jumps. For example, if upward and downward jumps are equally likely to occur, then skewness is always zero. However, 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.[13] Given the caveats of these measures, we choose to

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

[12]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).

[13]We have also calculated the skewness and kurtosis based on 5-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.

include the jump intensity, jump mean, and jump volatility measures as defined in equations (16)-(18). These measures combined can provide a full picture of the underlying jump risk.

4.2 Volatility and jump effects on credit spreads

Table 4 reports the main findings of OLS regressions, which explain credit spreads only by different measures of equity return volatility and/or jump measures. Regression (1) using 1-year historical volatility alone yields an 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. Regressions (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 give the best R-square result at 50%. The signs of coefficients are all correct—high volatility raises credit spread, and the magnitudes are all sensible—a 1 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 in that it includes both long-term and short-term equity volatilities, which is consistent with the theoretical prediction that equity volatility affects credit spreads via two factors (Hypothesis I). The existing literature usually adopts the long-term equity volatility, with the implicit assumption that equity volatility is constant over time. However, this assumption is problematic from the theoretical perspective. 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 nonlinear delta function. Within the stochastic volatility model (as discussed in Section 2), 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 but is important in determining credit spreads, as suggested by the substantial gains in the explanatory power and statistical significance of the short-run volatility coefficient.

Another contribution of our study 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 also has a correct sign (more jumps increase 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 measures is still very dismal—only 3% in R-square. In contrast, our new measures of jumps—regressions (5) to (7)—give significant estimates, and by themselves explain 19% of credit spread variations. A few points are worth mentioning. First, jump volatility has the strongest impact—raising default spread by 2.5-4.5 basis points for a 1 percentage point 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 0.6 basis point but negative jumps can increase spreads by 1.6 basis points. Hence, we will treat the two directions of jumps separately in the remaining part of this paper. Third, average jump size has only a muted impact (-0.2) and jump intensity can switch sign (from 0.55 to -0.97), which may be explained by controlling for positive or negative jumps.

Our new benchmark regression (8) explains 54% of credit spreads with volatility and jump variables alone, a very striking result compared with previous studies. The impacts of volatility and jump measures are in line with theoretical predictions and are economically significant as well. The gains in explanatory power relative to regression (1), which only includes long-run equity volatility, can be attributed to two causes. First, the decomposition of volatility into continuous and jump components, particularly recognizing the time variation in equity volatility and different aspects of jump risk, enables us to examine the different impacts of those variables in determining credit spreads, as laid out in hypotheses (1)-(4). Second, as shown in a recent study by Andersen et al. (2004), using lagged realized volatility and jump measures of different time horizons can significantly improve the accuracy of volatility forecast. Since the expected volatility and jump measures, which tend to be more relevant in determining credit spreads based on structural models, are not observable, empirical exercises typically have to rely on historical observations. Therefore, the gains in explanatory power might reflect the superior forecasting ability of our set of volatility and jump measures relative to historical volatility alone.

4.3 Extended regression with traditional controlling variables

We then include more explanatory variables—credit ratings, macro-financial conditions, and firms' balance sheet information—all of which are theoretical 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 volatilities and jumps in addition to ratings. Cossin and Hricko (2001) suggest that rating information is the single most important factor in determining CDS spreads. Indeed, our results confirm their findings that rating information alone explains about 56% of the variation in credit spreads, about the same as volatility and jump effects are able to explain (see Table 4). By comparing the rating dummy coefficients, apparently low-rating entities are priced significantly higher than high-rating ones, which is economically intuitive and consistent with the existing literature. By adding volatility and jump risk measures, we can explain another 18% of the variation (R^2 increases to 74%). All volatility and jump variables have the correct sign and are statistically very significant. More remarkably, the coefficients are more or less in the same magnitude as in the regression without rating information, except that the long-term historical volatility has a smaller impact.

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), firms' balance sheet information (ROE, firm leverage, and dividend payout ratio) and the recovery rate used by CDS price providers, combined explain an additional 7% of credit spread movements on top of rating information (regression (3) versus (1)). The combined impact increase is smaller than the volatility and jump effect (18%). Moreover, regression (4) suggests that the inclusion of volatility and jump effect provides another 14% of explanatory power compared to regression (3). R^2 increases to a very high level of 0.77. The results suggest that the volatility effect is independent of the impact of other structural or macro factors.

Overall, the jump and volatility effects are very robust, with the same signs and little change in magnitudes. To measure the economic significance more precisely, 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 about 50 and 40 basis points, respectively. For the jump component, a one standard deviation shock in JI, JV, JP and JN (41.0%, 16.5%, 92.9% and 93.4%) changes the credit spread by about 36, 26, 59, and 34 basis points, respectively. Adding them up, these factors could 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), macro-financial factors and firm variables have the expected signs. The market return has a significant negative impact on the spreads but the market volatility has a significantly positive effect, consistent with the business cycle effect. High profitability implies an upward movement in asset value and a lower default probability, and therefore has a negative impact on credit spreads. A high leverage ratio is linked to a shift in default boundary, with firms being more likely to default, while a high dividend payout ratio leads to a reduction in firm asset value, so both have positive impacts on credit spreads. For short-term rates and the term spread of yield curves, for which the theory does not give a clear answer, our regression shows that both have significantly positive effects, suggesting that the market is more likely to connect them with the change in monetary policy stance.

Another observation which should be emphasized is that the high explanatory power of rating dummies quickly diminishes 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), and the dummy effect across rating groups is less distinct. At the same time, the t-ratios for jump and volatility measures remain very high. This result is consistent with the rating agencies' practice of rating entities according to their accounting information and probably macroeconomic conditions as well.

4.4 Robustness check

We implement a robustness check by using a panel data technique with fixed and random effects (see Table 6). Although the 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. Moreover, the majority of macro-financial and firm accounting variables have consistent and significant impacts on credit spreads, except that firm profitability (ROE) and recovery rate become insignificant. 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.[14]

We also run the same regression using 1-year CDS spreads, provided by Markit as well.[15] All the structural factors, particularly the volatility and jump factors, affected credit spreads with the same signs and similar magnitude. Interestingly, the explanatory power of those structural factors on the short-maturity CDS spreads is close to the benchmark (regression (4) in Table 5). This is in contrast with the finding in the existing literature that structural models are less successful in explaining the short-maturity credit spreads. Such an improvement can be largely attributed to the inclusion of a jump process proxied by our jump measures, which allows the firm's asset value to change substantially over a short time horizon.

4.5 Estimation by rating groups

We have demonstrated that equity volatility and jump help to determine CDS spreads. The OLS regression is a linear approximation of the relationship between credit spreads and structural factors. However, structural models suggest that those coefficients are largely dependent on firms' fundamentals (asset value process, leverages, etc.), or the relationship can be nonlinear (Section 2.3). In the next two subsections we address these two issues, i.e., whether the impacts of structural factors are intimately related to firms' credit standing and accounting fundamentals, and whether the effect is nonlinear in nature.

We first examine whether the volatility and jump effects vary across different rating groups. Table 7 reports the benchmark regression results by dividing the sample into three rating groups: triple-A to single-A names, triple-B names, and high-yield entities. The explanatory power of structural factors is the highest for the high-yield group, consistent with the finding in Huang and Huang (2003). Nevertheless, structural factors explain 41% and 54% of the credit spread movements in the two investment grade groups, much higher than their study (below 20% and in the 30%s respectively).

The regression results show that the volatility/jump impact coefficients for

[14]We have also experimented with the Newey and West (1987) heteroscedasticity and autocorrelation (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 that so many firm-specific variables are included in the regressions.

[15]The results are not reported here but are available upon request.

high-yield entities are typically several times larger than those for the top investment grade names, and those for BBB entities in between. To be more precise, for long-run volatility the coefficients for the high-yield group and the top investment grade are 3.25 vs 0.75, short-run volatility 2.17 vs 0.36, jump intensity 1.52 vs 0.24, jump volatility 3.55 vs -0.03 (insignificant), positive jump -1.10 vs -0.13, and negative jump 0.52 vs 0.13. Similarly, the t-ratios of those coefficients in the former group are much larger than those in the top investment grade. If we also take into account the fact that high-yield names are associated with much higher volatility and jump risk (Table 3 and Figure 4), the economic implication of the interactive effect is even more remarkable.

At the same time, the coefficients of macro-financial and firm-specific variables are also very different across rating groups. Credit spreads of high-yield entities appear to respond more dramatically to changes in general equity market conditions. Similarly, the majority of firm-specific variables, including the recovery rate, the leverage ratio, and the dividend payout ratio, have a larger impact (both statistically and economically) on credit spreads in the low-rating group. Those results reinforce the idea that the impact of structural factors, including volatility and jump risks, depends on the firms' credit ratings and fundamentals.

4.6 The nonlinear effect

While the theory usually implies a complicated relationship between equity volatility and credit spreads, in empirical exercises a simplified linear relationship is often used. To test for the nonlinear relationship, we include the squared and cubic terms of volatility and jump variables, and the results are reported in Table 8.

The regression finds strong nonlinearity in the effect of long-run and short-run volatility, jump volatility, and positive and negative jumps, consistent with the prediction from hypotheses 1, 3, and 4 in Section 2.3. Moreover, in line with hypothesis 2, the regression suggests that the effect of jump intensity is more likely to be linear, as both squared and cubic terms turn out to be statistically insignificant.

Given that the economic implications of those coefficients are not directly interpretable, Figure 5 illustrates the potential impact of the nonlinear effect. The solid lines plot the pricing impact of 1-year and 1-month volatility, jump intensity, jump volatility, and positive and negative jumps, respectively, with each variable of interest ranging from its 5th and 95th percentile distributions. Compared with the calibration exercise as plotted in Figure 3, it is quite striking that the regression result fits extremely well with the model predictions. Volatility and jump measures both have convex nonlinear effects on credit spreads. The jump mean has an asymmetric impact, with negative jumps having larger pricing implications. The only difference lies in the impact of positive jumps, which increase credit spreads in the calibration but have an opposite effect in the regression. However, the positive relationship between credit spreads and positive jumps in the calibration might be due to the particular parameter values used in the example, and is more likely to be ambiguous from theoretical perspective (Table 1).

The existence of the nonlinear effect could have important implications for empirical studies. In particular, it suggests that the linear approximation can cause substantial bias in calibration exercises or the evaluation of structural models. This bias can arise from two sources, namely by assuming a linear relationship between credit spreads and structural factors or by using the group average of particular structural factors (the so-called Jensen inequality problem). The consequence of the former issue can be easily judged by comparing our regression results in Table 8 and Table 5, so here we mainly focus on the second issue.

We use an example in Huang and Huang (2003), in which they use the average equity volatility within a rating class in their calibration exercise, and find that the predicted credit spread is much lower than the observed value (average credit spreads in the rating class). The under-fitting of structural model predictions is also known as the credit premium puzzle. Nevertheless, this "averaging" of individual equity volatility could be problematic if its true impact on credit spread is nonlinear. The quantitative relevance of the Jensen inequality problem depends on the convexity of the relationship between the two variables.

Using our sample and regression results, the averaging of 1-year volatility can cause an under-prediction of credit spreads by 13 basis points.[16] Similarly, the averaging of 1-month volatility, jump volatility, and negative jumps will cause the calibrated value to be lower by 12, 3, and 4.5 basis points respectively. By contrast, the averaging of positive jumps causes an overestimation by about 7 basis points. The aggregate impact of this nonlinear effect is about 25 basis points, which is not trivial considering that the average CDS spread is 172 basis points. Even though this nonlinear effect explanation is not the only one that contributes to Huang and Huang's finding and may not be able to fully reconcile the disparity, it can

[16] The calculation is based on the difference between $F(E(HV), \Omega)$ and $E[F(HV, \Omega)]$, where $F(\cdot)$ refers to the estimated relationship between CDS spread and explanatory variables, and Ω refers to other structural factors.

perhaps point us in a promising direction for future research to address this issue.

5 Conclusions

In this paper we have extensively investigated the impact of theoretical 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 predicts an extra 14-18% of the total variation 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 the cross-sectional controls of fixed effect and random effect, suggesting that the temporal variations of credit spreads are adequately explained by the lagged structural explanatory variables. The volatility and jump effects are strongest for high-yield entities and financially stressed firms. Furthermore, these estimated effects exhibit strong nonlinearity, which is consistent with the implications from a structural model with stochastic volatility and jumps.

We adopted an innovative approach to identify the realized jumps of individual firms' equity, which enabled us to directly assess the impact of various jump risk measures (intensity, variance, and negative jump) on the default risk premia. These realized jump risk measures are statistically and economically significant, which contrasts with the typical mixed findings in the literature using historical or implied skewness as jump proxies.

Our study is only a first step towards improving our understanding of the impact of volatility and jumps on credit risk markets. Calibration exercises that take into account the time variation of volatility and jump risks and non-linear effects could be a promising area to explore in order to resolve the so-called credit premium puzzle. Related issues, such as rigorous specification tests of structural models with time-varying volatility and jumps, are also worth more attention from research professionals.

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.

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, 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.

Bakshi, Gurdip, Charles Cao, and Zhiwu Chen (1997), "Empirical performance of alternative option pricing models," *Journal of Finance*, vol. 52, 2003–2049.

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

Barndorff-Nielsen, Ole and Neil Shephard (2002), "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, 243–265.

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

Bates, David S. (1996), "Jumps and stochastic volatility: exchange rate process implicit in Deutsche Mark options," *Review of Financial Studies*, vol. 9, 69–107.

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.

Carr, Peter and Liuren Wu (2005), "Stock options and credit default swaps: a joint framework for valuation and estimation," *Working Paper*, Zicklin School of Business, Baruch College.

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.

Das, Sanjiv R. and Rangarajan K. Sundaram (2004), "A simple model for pricing securities with equity, interest-rate, and default risk," *Working Paper*, Santa Clara University.

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.

Duffie, Darrell, Jun Pan, and Kenneth Singleton (2000), "Transform analysis and asset pricing for affine jump-diffusions," *Econometrica*, vol. 68, 1343–1376.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann (2001), "Explaining the rate spread on corporate bonds," *Journal of Finance*, vol. 56, 247–277.

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 (2005), "The relative contribution of jumps to total price variance," *Journal of Financial Econometrics*, forthcoming.

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.

Jones, E. Philip, Scott P. Mason, and Eric Rosenfeld (1984), "Contingent claims analysis of corporate capital structures: an empirical investigation," *Journal of Finance*, vol. 39, 611–625.

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.

Madan, Dilip and Haluk Unal (2000), "A two-factor hazard rate model for pricing risky debt and the term structure of credit spreads," *Journal of Financial and Quantitative Analysis*, vol. 35, 43–65.

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.

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," *Journal of Banking and Finance*, vol. 28, 2813–2843.

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), Andersen et al. (2004), and Huang and Tauchen (2005) adopt test statistics of significant jumps based on the ratio statistics as defined in equation (14),

$$z = \frac{\mathrm{RJ}_t}{[((\pi/2)^2 + \pi - 5) \cdot \Delta \cdot \max(1, \frac{\mathrm{TP}_t}{\mathrm{BV}_t^2})]^{1/2}} \tag{20}$$

where Δ refers to the intra-day sampling frequency, BV_t is the bipower variation defined by equation (13), and

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

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 (2005) suggest using staggered returns to break the correlation in adjacent returns, an unappealing phenomenon caused by microstructure noise. In this paper we follow this suggestion and use the following generalized bipower measures ($j = 1$):

$$\mathrm{BV}_t \equiv \frac{\pi}{2} \sum_{i=2+j}^{1/\Delta} |r_{t,i}| \cdot |r_{t,i-(1+j)}|$$

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

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

$$\mathrm{RV(J)}_t = \sqrt{\mathrm{RV}_t - \mathrm{BV}_t} \cdot \mathrm{I}(z > \Phi_\alpha^{-1}) \tag{21}$$

$$\mathrm{RV(C)}_t = \sqrt{\mathrm{RV}_t} \cdot [1 - \mathrm{I}(z > \Phi_\alpha^{-1})] + \sqrt{\mathrm{BV}_t} \cdot \mathrm{I}(z > \Phi_\alpha^{-1}) \tag{22}$$

where RV_t is defined by equation (12), $\mathrm{I}(\cdot)$ is an indicator function and α is the chosen significance level. Based on the Monte Carlo evidence in Huang and Tauchen (2005) and Tauchen and Zhou (2005), we choose the significance level α as 0.999 with adjustment for microstructure noise.

B Data sources and definitions

The following variables are included in our study.

1. CDS data provided by Markit. We calculate average 5-year CDS spreads and recovery rates for each entity in every month.

2. Historical measures of equity volatility calculated from CRSP data. Based on the daily equity prices, we calculate average return, historical volatility (HV), historical skewness (HS), and historical kurtosis (HK) for each entity over 1-month, 3-month and 1-year time horizons.

3. Realized measures of equity volatility and jump. The data are provided by TAQ (Trade and Quote), which includes intra-day (tick-by-tick) transaction data for securities listed on the NYSE, AMES, and NASDAQ. The following measures are calculated over the time horizon of 1 month, 3,months and 1 year.

   - Realized volatility (RV): defined by equation (12).
   - Jump intensity (JI): the frequency of business days with non-zero jumps, where jumps are detected based on the ratio statistics (equation (14)) with the test level of 99.9% (see Appendix A for implementation detail).
   - Jump mean (JM) and jump variance (JS): the mean and the standard deviation of non-zero jumps.
   - Positive and negative jumps (JP and JN): the average magnitude of positive jumps and negative jumps over a given time horizon. JN is represented by its absolute term.

4. Firm balance sheet information. The accounting information is obtained from Compustat on a quarterly basis. We use the last available quarterly observation in regressions, and the three firm-specific variables are defined as follows (in percentages):

$$Leverage\ \ (LEV) = \frac{Current\ debt +\ Long\text{-}term\ debt}{Total\ equity\ +\ Current\ debt +\ Long\text{-}term\ debt}$$

$$ROE = \frac{Pre\text{-}tax\ income}{Total\ equity}$$

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

5. Four macro-financial variables collected from Bloomberg. They are: the S&P 500 average daily return and its volatility (in standard deviation terms) in the past six months, average short-term rate (3-month Treasury rate) and term spread (the difference between 10-year and 3-month Treasury rates) in the past month.

Table 1: **Theoretical predictions 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). A higher jump mean is linked to higher equity returns and therefore reduces the credit spread; nevertheless, there is a second-order positive effect as equity volatility also increases (see Section 2.3).
Expected recovery rates	Negative	Higher recovery rates reduce the present value of protection payments in the CDS contract.
Firm leverage	Positive	The Merton (1974) framework predicts that a firm defaults when its leverage ratio approaches 1. Hence credit spreads increase with leverage.
ROE	Negative	PD is lower when the firm's profitability improves.
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). Nevertheless, 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.

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	213	2.15
Consumer cyclical	63	20.52	AA	545	5.51
Consumer stable	55	17.92	A	2969	30.00
Energy	27	8.79	BBB	4263	43.07
Financial	23	7.49	BB	1280	12.93
Industrial	48	15.64	B	520	5.25
Materials	35	11.40	CCC	107	1.08
Technology	14	4.56			
Utilities	18	5.88			
Not specified	4	1.30			
Total	*307*	*100*	*Total*	*9897*	*100*
Firm-specific variables	**Mean**	**Std. dev.**	**Macro-financial variables**	**Mean (%)**	**Std. dev.**
Recovery rates (%)	39.50	4.63	S&P 500 return	-11.10	24.04
Return on equity (%)	4.50	6.82	S&P 500 vol	21.96	4.62
Leverage ratio (%)	48.84	18.55	3-M Treasury rate	2.18	1.36
Div. payout ratio (%)	0.41	0.46	Term spread	2.40	1.07
5-year CDS spread (bps)	172	230			

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

3.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

3.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

3.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

3.D Statistics by rating groups

	AAA to A		*BBB*		*BB and below*	
Variables	*mean*	*std dev*	*mean*	*std dev*	*mean*	*std dev*
CDS (bps)	52.55	39.98	142.06	130.28	536.18	347.03
1-year HV	36.38	11.28	40.07	13.40	62.41	25.97
1-month RV(C)	38.08	17.56	39.05	18.73	62.47	37.78
1-year JI	20.97	25.94	39.80	45.89	45.09	43.42
1-year JM	15.33	62.09	9.63	149.17	-31.14	310.46
1-year JS	20.63	12.39	24.51	13.50	35.60	22.81
1-year JP	64.00	51.97	99.39	80.10	156.90	128.11
1-year JN	61.54	51.86	91.34	73.78	162.77	132.35

Notes: (1) Throughout 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); (3) JI, JM, JV, JP, and JN refer to the jump intensity, jump mean, jump standard deviation, positive jumps, and negative jumps, respectively, as defined in Section 2. Note that negative jumps are defined in absolute terms.

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

	Dependent variable: 5-year CDS spread (in basis points)							
Explanatory variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Constant	-207.22	-91.10	-223.11	147.35	42.05	85.66	51.93	-272.08
	(36.5)	(18.4)	(40.6)	(39.6)	(8.2)	(20.8)	(10.0)	(44.4)
1-year HV	9.01		6.51					6.56
	(72.33)		(40.2)					(40.7)
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)								2.58
								(22.3)
1-year JI					0.55		-0.97	1.46
					(7.0)		(7.0)	(13.4)
1-year JM					-0.21			
					(14.9)			
1-year JV					4.52		2.51	1.32
					(28.2)		(10.3)	(7.2)
1-year JP						-0.45	-0.59	-0.63
						(7.3)	(8.2)	(11.7)
1-year JN						1.47	1.59	0.46
						(22.9)	(22.7)	(8.3)
Adjusted R^2	0.45	0.37	0.50	0.03	0.15	0.14	0.19	0.54
Obs.	6342	6353	6337	6342	6328	6328	6328	6328

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

Table 5: **Regressions with ratings, individual equity volatilities and 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			-0.87	(18.7)			-0.75	(15.8)
1-year HV			2.09	(14.4)			2.79	(18.1)
1-month RV(C)			2.14	(21.6)			1.60	(14.9)
1-year JI			0.93	(10.3)			0.89	(9.4)
1-year JV			1.29	(8.9)			1.58	(11.0)
1-year JP			-0.69	(15.8)			-0.63	(14.8)
1-year JN			0.39	(8.6)			0.36	(8.4)
Rating (AAA)	33.03	(2.1)	-160.81	(11.1)	-72.09	(1.9)	-342.99	(11.1)
Rating (AA)	36.85	(4.6)	-143.36	(18.2)	-81.66	(2.3)	-332.93	(11.3)
Rating (A)	56.62	(15.9)	-126.81	(21.7)	-68.62	(2.0)	-320.11	(11.1)
Rating (BBB)	142.06	(49.9)	-60.04	(9.4)	9.31	(0.3)	-258.11	(8.9)
Rating (BB)	436.94	(73.4)	158.18	(18.1)	294.02	(8.4)	-46.14	(1.6)
Rating (B)	744.95	(77.1)	376.90	(29.7)	556.58	(15.9)	127.03	(4.1)
Rating (CCC)	1019.17	(34.9)	583.74	(22.1)	566.83	(9.9)	9.31	(0.2)
S&P 500 return					-1.21	(11.1)	-0.82	(8.9)
S&P 500 vol					4.87	(8.4)	0.88	(1.8)
Short rate					13.46	(3.1)	15.52	(4.5)
Term spread					33.38	(6.0)	42.30	(9.5)
Recovery rate					-2.65	(-5.4)	-0.59	(1.5)
ROE					-4.20	(14.3)	-0.79	(3.3)
Leverage ratio					0.46	(4.1)	0.68	(7.6)
Div. payout ratio					12.84	(3.0)	21.52	(6.0)
Adjusted R^2	0.56		0.74		0.63		0.77	
Obs.	6055		5950		4989		4952	

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			-0.85	(19.8)			-0.83	(19.7)
1-year HV	3.09	(19.2)	1.58	(9.4)	3.54	(23.0)	1.88	(11.5)
1-month RV(C)	2.74	(34.8)	1.58	(18.5)	2.74	(34.9)	1.60	(18.8)
1-year JI	0.21	(1.5)	0.15	(1.1)	0.43	(3.2)	0.35	(2.6)
1-year JV	1.06	(6.9)	1.35	(9.5)	1.01	(6.7)	1.35	(9.7)
1-year JP	-0.69	(14.6)	-0.55	(12.3)	-0.65	(14.0)	-0.53	(12.2)
1-year JN	0.46	(8.5)	0.34	(6.7)	0.54	(10.4)	0.40	(8.3)
Rating (AAA)			-203.65	4.9)			-375.58	(9.3)
Rating (AA)			-230.48	(7.8)			-393.30	(12.3)
Rating (A)			-165.49	(7.2)			-330.47	(11.8)
Rating (BBB)			-133.47	(6.5)			-281.13	(10.1)
Rating (BB)			-110.64	(6.5)			-207.16	(7.1)
Rating (B)							-62.38	(1.9)
Rating (CCC)							-40.67	(0.4)
S&P 500 return			-0.80	(11.4)			-0.81	(11.5)
S&P 500 vol			0.44	(1.2)			0.63	(1.7)
Short rate			16.31	(5.9)			17.80	(6.5)
Term spread			40.78	(11.8)			41.90	(12.2)
Recovery rate			-0.13	(0.4)			-0.21	(0.6)
ROE			0.02	(0.1)			-0.09	(0.4)
Leverage ratio			2.52	(9.0)			2.23	(9.6)
Div. payout ratio			45.23	(9.1)			42.89	(8.9)
Adjusted R^2	0.81		0.87		–		–	
Obs.	6328		4952		6328		4952	

Table 7: **Regressions by rating groups**

	Group 1 (AAA, AA, and A)		**Group 2** (BBB)		**Group 3** (High-yield)	
Regression	*coef*	*t-stat*	*coef*	*t-stat*	*coef*	*t-stat*
Constant	-109.87	(8.0)	-347.00	(9.7)	-351.10	(2.8)
1-year return	-0.12	(3.5)	-0.61	(9.3)	-0.76	(5.9)
1-year HV	0.75	(6.8)	3.81	(17.8)	3.25	(8.3)
1-month RV(C)	0.36	(5.8)	1.38	(9.9)	2.17	(6.5)
1-year JI	0.24	(3.6)	0.30	(2.6)	1.52	(4.4)
1-year JV	-0.03	(0.3)	0.06	(0.2)	3.55	(9.4)
1-year JP	-0.13	(4.0)	-0.31	(5.6)	-1.10	(9.0)
1-year JN	0.13	(4.7)	0.60	(9.4)	0.52	(4.3)
S&P 500 return	-0.41	(9.4)	-1.29	(11.4)	-1.69	(4.0)
S&P 500 vol	0.54	(2.5)	0.31	(0.5)	6.46	(3.0)
Short rate	9.95	(6.1)	14.48	(3.4)	-12.12	(0.7)
Term spread	19.03	(9.2)	48.02	(8.8)	59.10	(2.9)
Recovery rate	0.61	(3.0)	1.11	(2.2)	-5.32	(3.8)
ROE	-1.19	(9.5)	-1.85	(5.9)	1.23	(1.4)
Leverage ratio	0.20	(5.5)	0.54	(4.3)	5.19	(11.1)
Div. payout ratio	16.45	(8.1)	24.17	(6.1)	59.83	(3.6)
Adjusted R^2	0.41		0.54		0.65	
Obs.	1881		2311		760	

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

Variables	*coef*	*t-stat*
1-year return	-0.73	(15.8)
HV	-5.47	(6.8)
HV^2	2.04	(11.7)
HV^3	-0.13	(12.4)
RV(C)	-1.60	(4.2)
$RV(C)^2$	0.44	(7.1)
$RV(C)^3$	-0.01	(3.9)
JI	0.68	(1.5)
JI^2	-0.09	(1.2)
JI^3	0.006	(1.2)
JV	-0.14	(0.3)
JV^2	0.27	(3.1)
JV^3	-0.01	(2.8)
JP	0.02	(0.1)
JP^2	-0.04	(3.2)
JP^3	0.0007	(2.7)
JN	0.02	(0.1)
JN^2	0.06	(4.8)
JN^3	-0.002	(5.5)
Rating (AAA)	-134.10	(4.2)
Rating (AA)	-128.08	(4.2)
Rating (A)	-112.64	(3.8)
Rating (BBB)	-49.84	(1.7)
Rating (BB)	159.28	(5.2)
Rating (B)	300.55	(9.7)
Rating (CCC)	282.89	(5.8)
S&P 500 return	-0.97	(10.8)
S&P 500 vol	2.04	(4.47)
3M Treasury rate	16.26	(4.9)
Term spread	40.48	(9.6)
Recovery rate	-0.44	(1.2)
ROE	-0.91	(3.9)
Leverage ratio	0.69	(8.2)
Div. payout ratio	18.22	(5.4)
Adjusted R^2	0.80	
Obs.	4952	

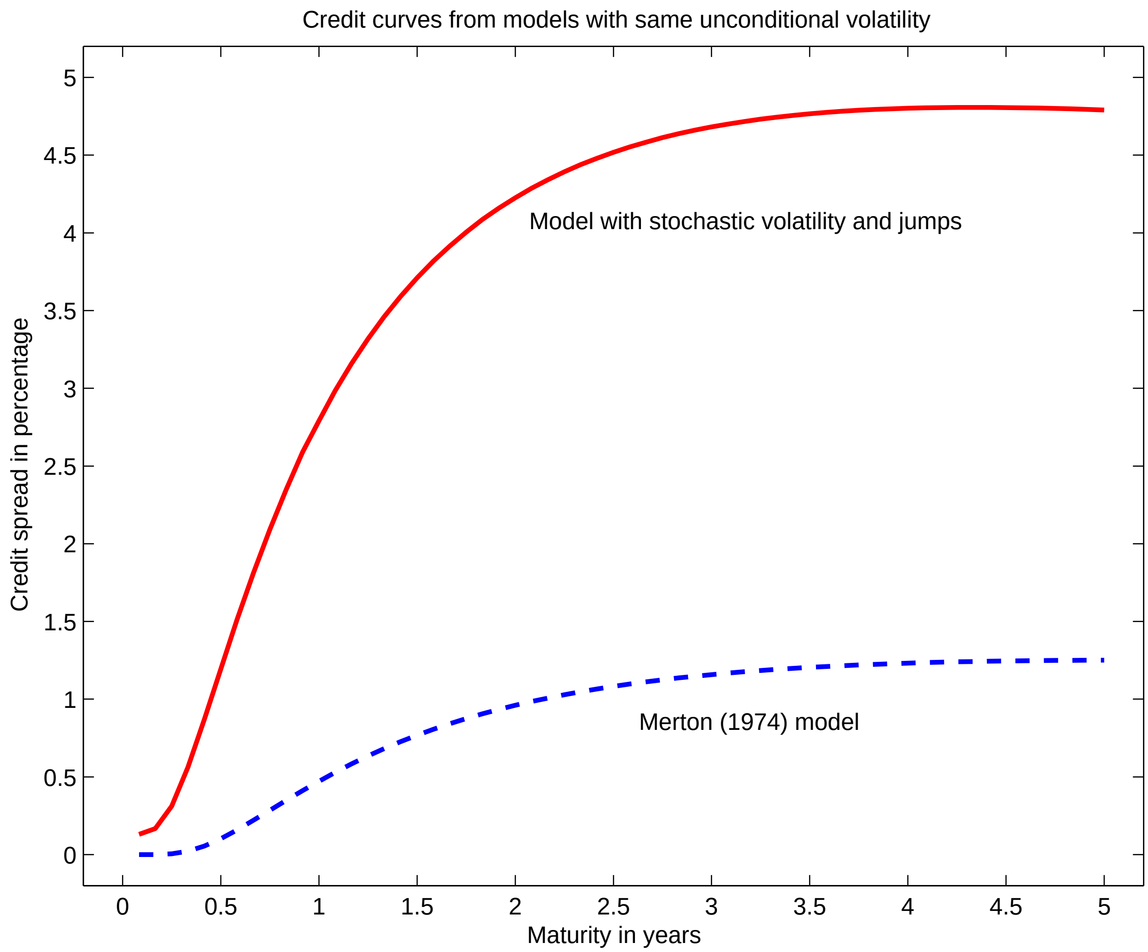

Figure 1: Credit curves

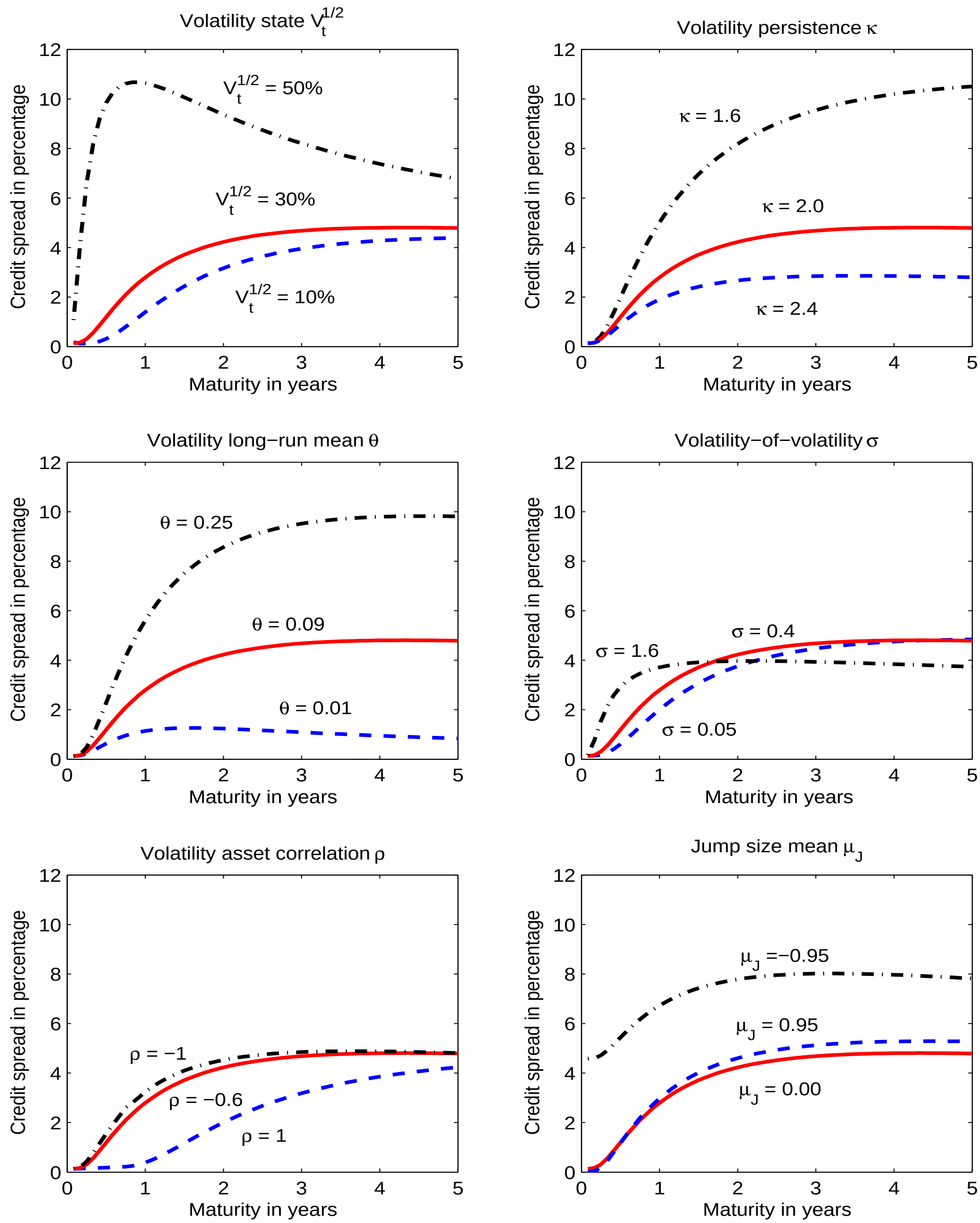

Figure 2: Comparative statics with volatility and jump parameters

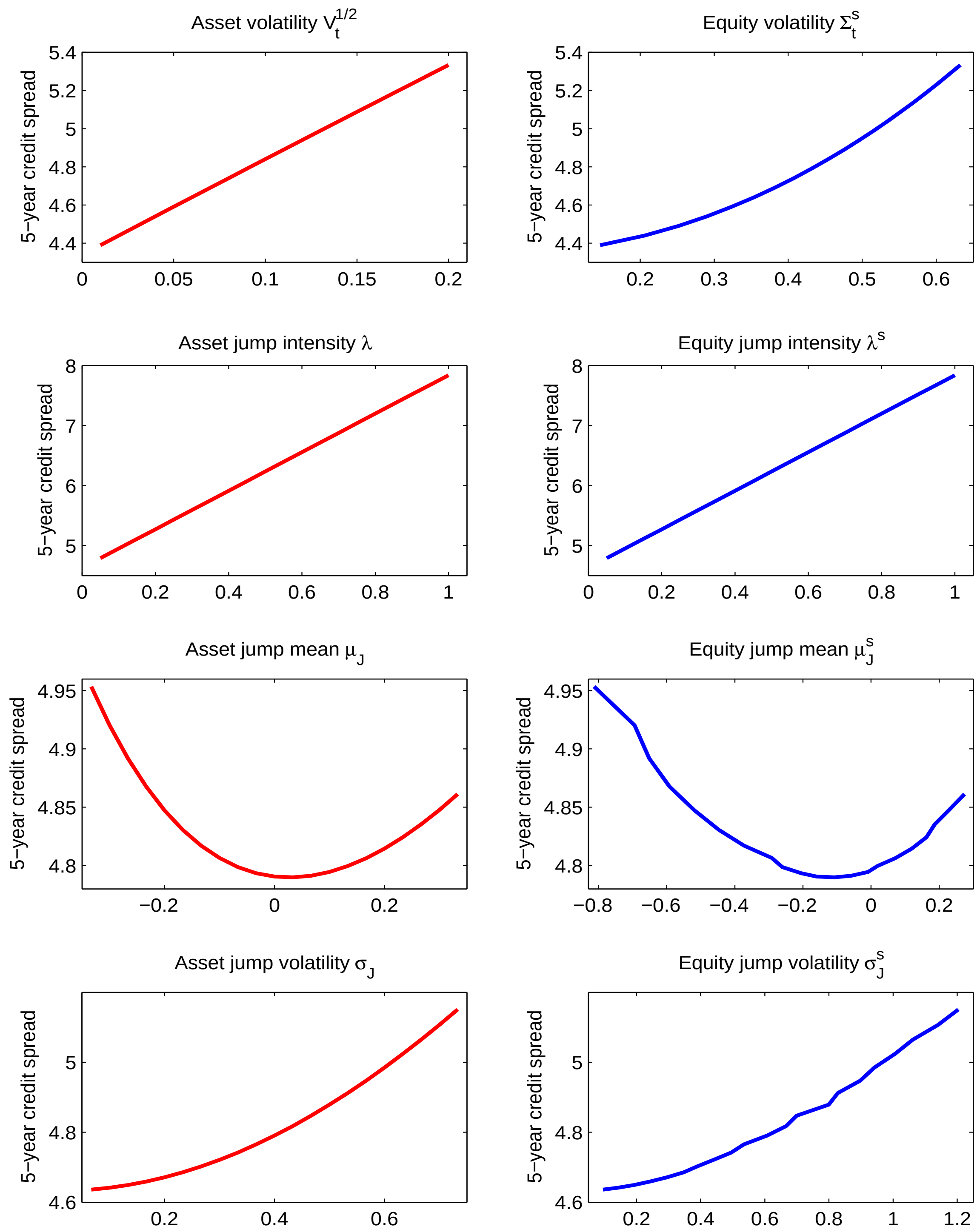

Figure 3: Linkages from asset and equity values to credit spreads

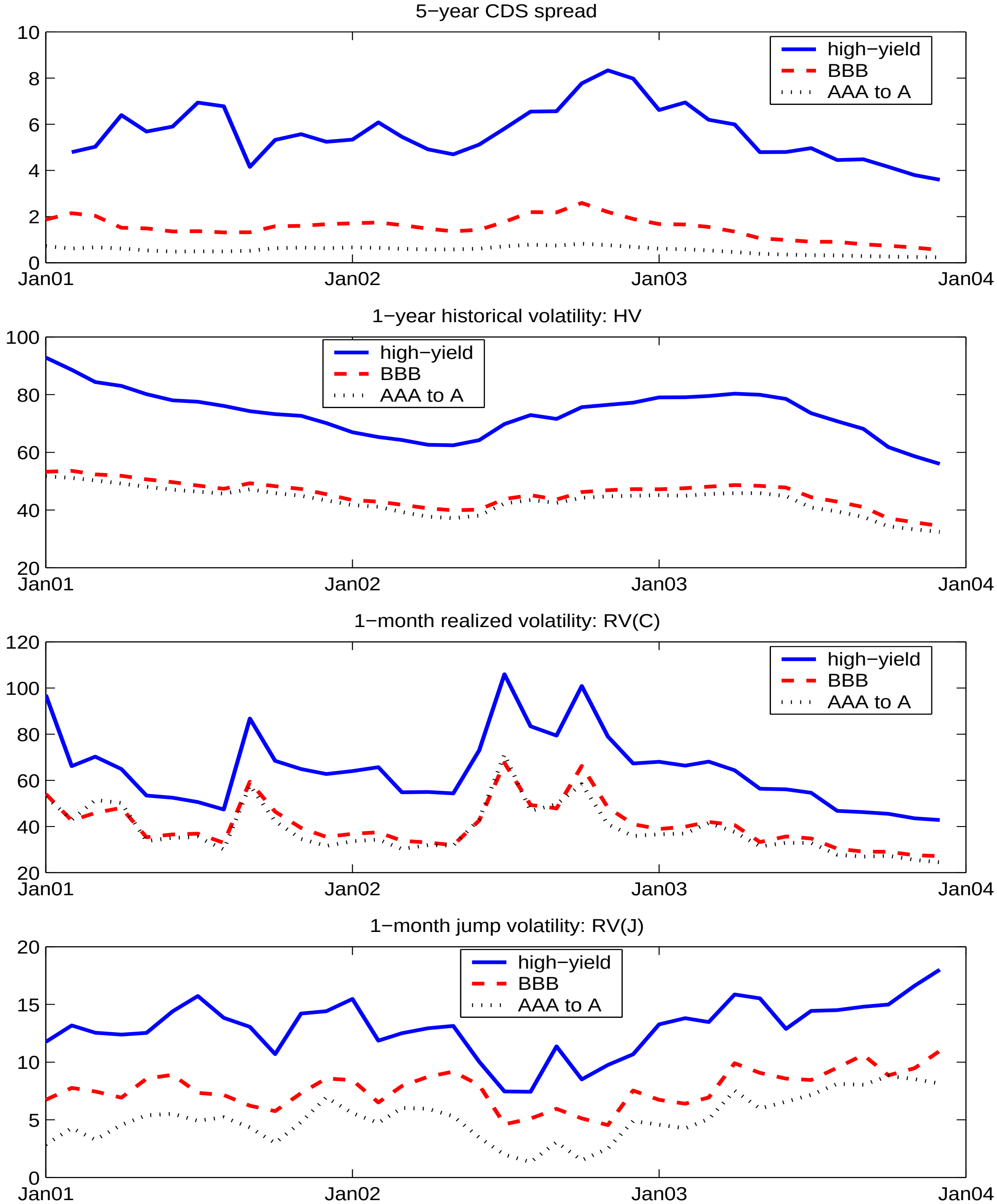

Figure 4: CDS spreads and volatility risks by rating groups

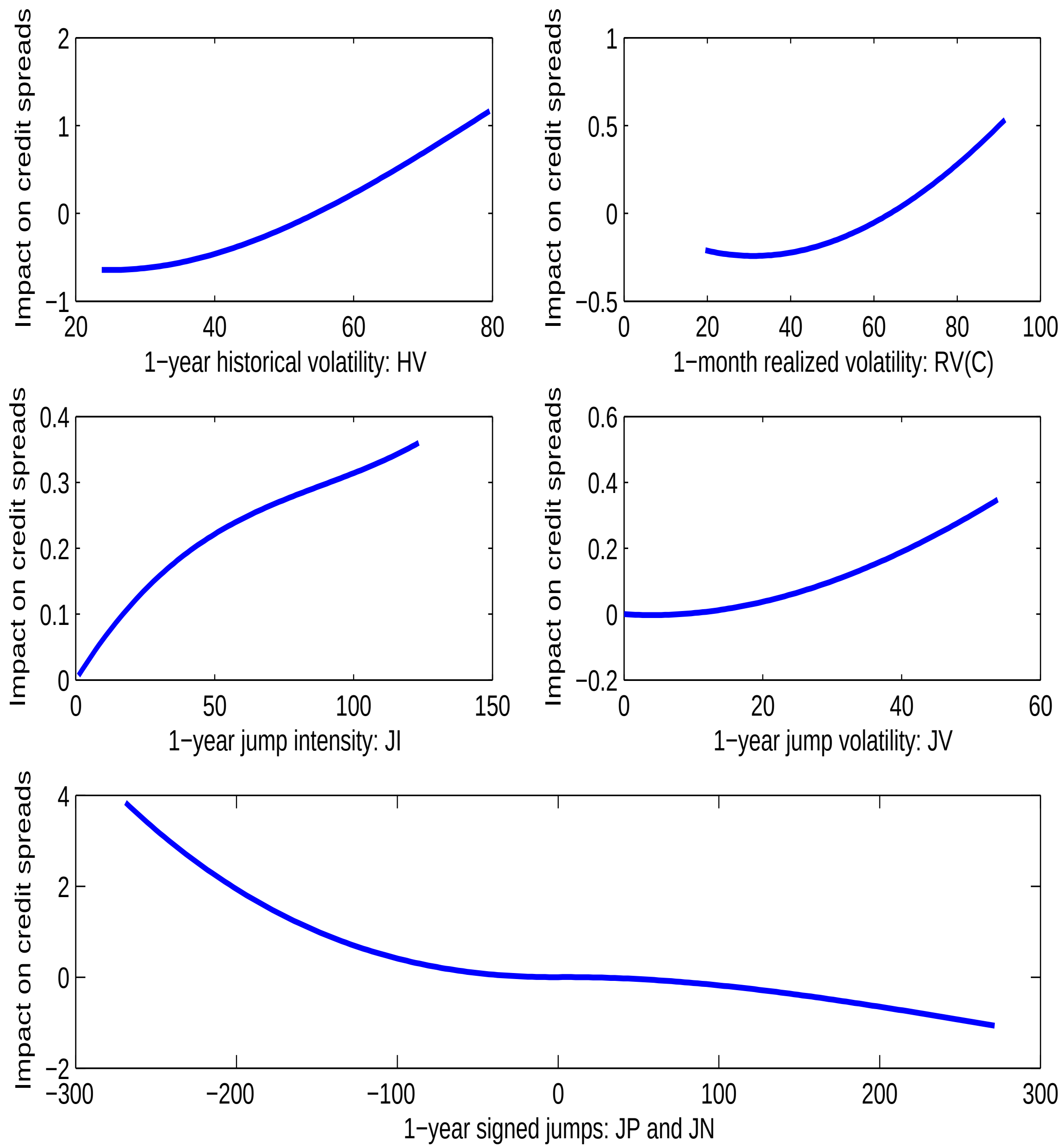

Figure 5: Nonlinear effect of individual volatility

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.