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

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Abstract

A structural model with stochastic volatility and jumps implies specific 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 equities from high frequency data. Our empirical results suggest that volatility risk alone predicts 50 percent of the variation in CDS spreads, while jump risk alone forecasts 19 percent. After controlling for credit ratings, macroeconomic conditions, and firms' balance sheet information, we can explain 77 percent of the total variation. Moreover, the pricing effects of volatility and jump measures vary consistently across investment-grade and 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.

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Abstract

A structural model with stochastic volatility and jumps implies specific 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 equities from high frequency data. Our empirical results suggest that volatility risk alone predicts 50 percent of the variation in CDS spreads, while jump risk alone forecasts 19 percent. After controlling for credit ratings, macroeconomic conditions, and firms' balance sheet information, we can explain 77 percent of the total variation. Moreover, the pricing effects of volatility and jump measures vary consistently across investment-grade and 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.

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1 Introduction

The empirical tests of structural models of credit risk indicate that such models have been unsuccessful. Methods of strict estimation or calibration provide evidence that the models are deficient: Predicted credit spreads are far below observed ones (Jones, Mason, and Rosenfeld, 1984), the structural variables explain little of the credit spread variation (Huang and Huang, 2003), and pricing error is large for corporate bonds (Eom, Helwege, and Huang, 2004). More flexible regression analysis, although confirming the validity of the cross-sectional or long-run factors in predicting the bond spread, suggests that the power of default risk factors to explain the credit spread is still small (Collin-Dufresne, Goldstein, and Martin, 2001). Regression analysis also indicates that the temporal changes in the bond spread are not directly related to expected default loss (Elton, Gruber, Agrawal, and Mann, 2001) and that the forecasting power of long-run volatility cannot be reconciled with the classical Merton model (1974) (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, Sundaresan, and Tychon, 1996; Mella-Barral and Perraudin, 1997), and mean-reverting leverage ratios (Collin-Dufresne and Goldstein, 2001).

To address these negative findings, we propose a novel approach for explaining credit spread variation. We argue that incorporating stochastic volatility and jumps into 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 the volatility coefficient is clearly inconsistent with the structural model of constant volatility (Merton, 1974). Nevertheless, in theory incorporating jumps, should lead to a better explanation of the level of credit spreads for investment-grade bonds at short maturities (Zhou, 2001), but the empirical evidence is rather mixed. Collin-Dufresne, Goldstein, and Martin (2001) and Collin-Dufresne, Goldstein, and Helwege (2003) use a market-based jump-risk measure and find that it explains only a very small proportion of the credit spread. Cremers, Driessen, Maenhout, and Weinbaum (2004a,b) instead rely on individual option-implied skewness and find some positive evidence. We demonstrate numerically that adding stochastic volatility and jumps to the classical Merton model (1974) can dramatically increase the flexibility of the entire credit curve, potentially enabling the model to better match observed yield spreads and to better forecast temporal variation. In particular, we outline the testable empirical hypotheses concerning the relationships between the observable equity returns and observable credit spreads implied by the underlying asset-return process. This step is important, as asset value and volatility are generally not observable and the testing of structural models must rely heavily on the observable equity return and observable default spread.

Our methodology builds on the recent literature on measuring volatility and jumps from high-frequency data. We adopt both historical and realized measures as proxies for the temporal variation in equity returns, and we adopt realized jump measures as proxies for various aspects of jump risk. Our main 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 than from low-frequency data (Andersen, Bollerslev, Diebold, and Labys, 2001; Barndorff-Nielsen and Shephard, 2002; Meddahi, 2002). Furthermore, the contributions of the continuous and jump components of realized variance can be separated by analyzing the difference between bipower variation and quadratic variation (Barndorff-Nielsen and Shephard, 2004; Andersen, Bollerslev, and Diebold, 2005; Huang and Tauchen, 2005). Considering that jumps on financial markets are usually rare and large, we further assume that (1) there is at most one jump per day and (2) jump size dominates daily return when it occurs. These assumptions help us to identify the daily realized jumps of equity returns, as in Tauchen and Zhou (2005). From these realized jumps, we can estimate the jump intensity, jump mean, and jump volatility, and we can directly test the connections between equity returns and credit spreads implied by a stylized structural model that has incorporated stochastic volatility and jumps into the asset-value process.

The empirical success of our approach also depends on a direct measure of credit default spreads. For this measure, we rely on the credit default swap (CDS) premium, the most popular instrument in the rapidly growing credit derivatives market. Compared with corporate bond spreads, which were widely used in previous studies in tests of structural models, CDS spreads have two important advantages. First, CDS spreads provide relatively pure pricing of the default risk of the underlying entity. The contracts are typically traded on standardized terms. In contrast, bond spreads are more likely to be affected by differences in contractual arrangements, such as differences related to seniority, coupon rates, embedded options, and guarantees. For example, Longstaff, Mithal, and Neis (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, Brennan, and March (2005) and Zhu (2004) show that, although CDS spreads 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. Part of the reason for the quicker response of CDS spreads may be that they are unfunded and do not face short-sale restrictions. The fact that CDS leads the bond market in price discovery is integral to our improved explanation of the temporal changes in credit spread by default-risk factors.

There is a subtle difference between our empirical regression approach and the ones used in previous studies. In contrast to the common empirical strategy that simultaneously regresses credit spreads on structural variables constructed from equity or option data, we use only the lagged explanatory variables. Under a typical structural framework, only asset return and asset volatility are exogenous processes, whereas equity return and equity volatility as well as credit spread are all endogenously determined. Simultaneous regressions without structural restrictions would artificially inflate the R^2 values 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 effects on credit spreads. Realized jump measures explain 19 percent of total variations in credit spreads, whereas measures of the historical skewness and historical kurtosis of jump risk explain only 3 percent. Notably, volatility and jump risks alone can predict 54 percent of the spread variations. After controlling for credit ratings, macro-financial variables, and firms' accounting information, we find that the signs and significance of the jump and volatility effects remain solid, and the R^2 increases to 77 percent. These results are robust to whether the fixed effect or the random effect is taken into account, an indication that the temporal variation of default-risk factors does explain CDS spreads. More important, the sensitivity of credit spreads to volatility and jump risk is greatly elevated from investment-grade to high-yield entities, a finding that has implications for managing the more risky credit portfolios. Last but not least, both the volatility-risk and the jump-risk measures show strong nonlinear effects; this result is consistent with the hypotheses implied by the structural model that has incorporated stochastic volatility and jumps.

The remainder of the paper is organized into four sections. Section 2 introduces the structural link between equity and credit and discusses the methodology for disentangling volatility and jumps through the use of high-frequency data. Section 3 then gives a brief description of the CDS data and the structural explanatory variables. Section 4 presents the main empirical findings regarding the role of jump and volatility risks in explaining credit spreads. Section 5 summarizes the findings and proposes avenues of future research.

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 prices and volatilities have been a common practice. However, because the equity shares and credit derivatives of many listed firms are traded in relatively liquid markets, researchers are prompted to directly model the observable equity dynamics to explain and predict the credit spreads (see, Madan and Unal, 2000; Das and Sundaram, 2004; Carr and Wu, 2005, among others). Nevertheless, structural models can still provide important economic intuitions to interpret the empirical linkage between equity and credit. Here we motivate our empirical exercise by using an affine structural model to examine the model-implied equity-credit relationship.

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) into the underlying firm-value process:

$$\begin{aligned} \frac{dA_t}{A_t} &= (\mu - \delta - \lambda\mu_J)dt + \sqrt{V_t}dW_{1t} + J_t dq_t, && (1) \\ dV_t &= \kappa(\theta - V_t)dt + \sigma\sqrt{V_t}dW_{2t}, && (2) \end{aligned}$$

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 $(dW_{1t}, dW_{2t}) = \rho$. This specification has been extensively studied in the equity-option pricing literature (see Bates, 1996; Bakshi et al., 1997, for example). To be suitable for pricing corporate debt, the required assumptions are that default occurs only at maturity with a fixed default boundary and that when default occurs, there is no bankruptcy cost and the absolute priority rule prevails (Huang, 2005).

Using the no-arbitrage solution method of Duffie, Pan, and Singleton (2000), one can solve the equity price S_t as a European call option on debt D_t with face value B and maturity time T:

$$S_t = A_t F_1^* - Be^{-r(T-t)} F_2^*, \tag{3}$$

where F_1^* and F_2^* are so-called risk-neutral probabilities.[1] 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

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

where R_t is the risky interest rate and r is the risk-free interest rate.

2.2 The sensitivity of credit spread to asset volatility and jumps

We analyze the effect of stochastic volatility and jumps on credit spread. We plot (in Figure 1) the credit yield curves from both the Merton model (1974) and the jump diffusion stochastic volatility (JDSV) model; the models' equity-return volatilities match those of the high-yield entities.[2] The five-year credit spread of the JDSV model is 479 basis points, similar to the speculative grade spread observed in our sample, where as the five-year credit spread of Merton's model is 144 basis points, close to the investment-grade spread. This difference highlights the finding that Merton's model typically underfits the observed bond spread (Jones, Mason, and Rosenfeld, 1984), whereas introducing time-varying volatility here clearly produces a higher credit spread. Incorporating jumps allows the short end of the yield curve (one month) 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 seen in Figure 2). The high-volatility state, $V_t^{1/2}$, increases credit spread very dramatically at shorter maturities of less than one year, and the credit curve becomes inverted when the volatility level is high (50 percent). High mean reversion of volatility, κ, reduces spread (less persistent), whereas the high long-run mean of volatility, θ, increases spread (more risky). However, the volatility-of-volatility, σ, and the volatility-asset correlation, ρ, have rather muted effects on spread, and the effect signs are not uniform across

[1] Assuming no-arbitrage, one can specify the corresponding the risk-neutral dynamics as

$$\begin{aligned} \frac{dA_t}{A_t} &= (r - \delta - \lambda^*\mu_J^*)dt + \sqrt{V_t}dW_{1t}^* + J_t^* dq_t^*, & (4) \\ dV_t &= \kappa^*(\theta^* - V_t)dt + \sigma\sqrt{V_t}dW_{2t}^*, & (5) \end{aligned}$$

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 $\mu_J^* = \mu_J + \xi_J$.

[2] The parameter values are chosen as $r = 0.05$, $T - t = 5$, $B/A_t = 0.6$, $\mu = 0$, $\delta = 0$; $V_t = 0.09$, $\kappa = 2$, $\theta = 0.09$, $\sigma = 0.4$, $\rho = -0.6$; $\lambda = 0.05$, $\mu_J = 0$, $\sigma_J = 0.4$; $\xi_v = -1.2$, $\xi_\lambda = 0$, $\xi_J = 0$. This setting is similar to several scenarios examined in Longstaff and Schwartz (1995) and Zhou (2001); therefore, we report only the comparative statics that are not reported in the previous studies. The unconditional asset volatility $\sqrt{\theta + \lambda\sigma_J^2} = 0.313$ is the same across both the JDSV model and the Merton model (1974). The values of κ, σ, and ρ are adapted from Bakshi, Cao, and Chen (1997).

all maturities. Finally, the jump mean, μ_J, seems to have nonmonotonic and asymmetric effects on credit spread – that is, both positive and negative jump means will elevate the credit spread, but negative jump means seem to raise the spread higher.[3]

2.3 Testable hypotheses relating equity to credit

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

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

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,

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

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

where J_t^s has unconditional mean μ_J^s and standard deviation σ_J^s, which are unknown in closed form because of 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, whereas the asset volatility is simply driven by V_t. However, if asset volatility is constant (V), then equation (8) reduces to the standard Merton formula (1974), $\Sigma_t^s = \sqrt{V}\frac{\partial S_t}{\partial A_t}\frac{A_t}{S_t}$. Because the Poisson driving process is the same for equity jump as it is for asset jump, it has the same intensity function: $\lambda^s = \lambda$.

The most important empirical implication is how *credit* spread responds to changes in *equity* jump and *equity* volatility parameters, implied by the underlying changes in *asset* jump and *asset* volatility parameters (Figure 3). The left column suggests that five-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. More interestingly, the effect is nonlinear and asymmetric—the negative jump

[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 effects on credit spreads are the same as the effects of those parameters and are hence omitted. In addition, the positive effects of jump intensity, λ, and jump volatility, σ_J, on credit spread are similar to the effects reported in Zhou (2001) and are hence omitted.

mean increases spread much more than does the positive jump mean. The reason is that 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 because of the lognormal jump distribution.

Given the same changes in structural asset volatility and asset jump parameters, the right column in Figure 3 plots credit spread changes as related to the *equity* volatility and *equity* jump 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 because of 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 effect on credit spread, but the range of equity jump volatility is nearly twice as large as that of asset jump volatility. Equity jump mean (μ_J^s) also has a nonlinear, asymmetric effect on credit spread, but the equity jump mean is more negative than the asset jump mean.[4] Of course, in a linear regression setting, one would find only the approximate negative relationship between equity jump mean and credit spread. These relationships, illustrated in Figure 3, are qualitatively robust to alternative settings of the structural parameters.

To summarize, the following empirical hypotheses may be tested regarding the relationship 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 volatility increases credit spread nonlinearly*
- *H4 Equity jump mean affects credit spread in a nonlinear, asymmetric way; negative jumps tend to have larger effects.*

2.4 Disentangling the jump and volatility risks of equities

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

[4]Equity jump mean, μ_J^s, and standard deviation, σ_J^s, do not have closed-form solutions. So at each grid of the structural parameter values μ_J and σ_J, we simulate asset jump 2000 times and use equation (9) to numerically evaluate μ_J^s and σ_J^s.

Let $s_t \equiv \log S_t$ denote the time t logarithmic price of the stock, which evolves 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 $r_t^s \equiv s_t - s_{t-1}$. We have designated historical volatility, defined as the standard deviation of daily returns, as one proxy for the volatility risk of the underlying asset-value process (see, for example, Campbell and Taksler, 2003). The intraday returns are defined as follows:

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

where $r_{t,i}^s$ 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, Bollerslev, and Diebold (2005), and Huang and Tauchen (2005). Here we adopt the ratio test statistics, defined as follows:

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

[5] That is, $1/\Delta$ observations occurs on every trading day. Typically, the five-minute frequency is used because more frequent observations may be subject to distortion from market microstructure noise (Aït-Sahalia, Mykland, and Zhang, 2005; Bandi and Russell, 2005).

When appropriately scaled by its asymptotic variance, $z = \frac{\mathrm{RJ}_t}{\sqrt{\mathrm{Avar}(\mathrm{RJ}_t)}}$ converges to a standard normal distribution.[6] This test tells us whether a jump occurred during a particular day and how much jump contributes to the total realized variance – that is, 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, Bollerslev, and Diebold (2005), 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, this method of identifying realized jumps and estimating jump parameters yields reliable results in finite samples as the sample size increases and as the sampling interval shrinks. We can also estimate the time-varying jump parameters for a rolling window, for example, $\hat{\lambda}_t^s$, $\hat{\mu}_{J,t}^s$, and $\hat{\sigma}_{J,t}^s$ over a one-year horizon. Equipped with this econometric technique, we are ready to re-examine the effect 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. The CDS is the most popular instrument in the rapidly growing credit derivatives market. Under a CDS contract, the protection 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

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

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 the 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. Using the contributed quotes, Markit creates the daily composite quote for each CDS contract.[8] Together with the pricing information, the data set also reports average recovery rates used by data contributors in pricing each CDS contract.

In this paper, we include all CDS quotes written on U.S. entities (excluding sovereign entities) and denominated in U.S. dollars. We eliminate the subordinated class of contracts because of their small relevance in the database and their unappealing implications for credit risk pricing. We focus on five-year CDS contracts with modified restructuring (MR) clauses, as they are the most popularly traded in the U.S. market.[9] After matching the CDS data with other information, such as equity prices and balance sheet information (discussed later), we are left with 307 entities in our study. This much larger pool of constituent entities relative to the pools in previous studies makes us 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 those observations for which huge discrepancies (above 20 percent) exist between CDS spreads with modified restructuring clauses and those with full restructuring clauses. In addition, we also remove those CDS spreads that are

[7]There has been a growing interest in examining the pricing determinants of credit derivatives and bond markets (Cossin and Hricko, 2001; Ericsson, Jacobs, and Oviedo, 2005; Houweling and Vorst, 2005) and the role of CDS spreads in forecasting future rating events (Hull, Predescu, and White, 2003; Norden and Weber, 2004).

[8]Markit adopts three major filtering criteria to remove potential measurement errors: (1) an outlier criterion, which removes quotes that are far above or far below the average prices reported by other contributors; (2) a staleness criterion, which removes contributed quotes that exhibit no change for a long period; and (3) a term structure criterion, which removes flat curves from the data set.

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

[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 likely to understate the effect of firms' balance sheets on CDS pricing. Second, as most CDS contracts are infrequently traded, the CDS data suffer significantly 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 that the standard ordinary least squares (OLS) regression is a suitable tool in our empirical analysis.

higher than 20 percent because they are often associated with the absence of trading or a bilateral arrangement for 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. We provide the definitions and sources of those variables (Appendix B), and we formulate theoretical predictions of their effects on credit spreads (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 intraday equity prices. We calculate the two volatility measures over different time horizons (one-month, three-month, and one-year) to create proxies for the time variation in equity volatility. We also define jumps on each day on the basis of ratio test statistics (equation (14)) with the significance level of 0.999 (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, we include in our firm-specific variables the firm leverage ratio (LEV), the return on equity (ROE), and the dividend payout ratio (DIV). And we use four macro-financial variables as proxies for the overall state of the economy: (1) the S&P 500 average daily return (past six months), (2) the volatility of S&P 500 return (past 6 months), (3) the average three-month Treasury rate, and (4) the slope of the yield curve (ten-year minus three-month).

4 Empirical evidence

In this section, we first briefly describe the attributes of our volatility and jump measures, and then we examine their role in explaining movements in CDS spreads. The benchmark regression is an ordinary least square (OLS) test that pools together all valid observations:

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

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

Note that we use only lagged explanatory variables, mainly to avoid the simultaneity problem. Viewed from a structural perspective, most explanatory variables, such as equity return and volatility, ratings, and option-implied volatility and skewness as used in

Cremers, Driessen, Maenhout, and Weinbaum (2004a,b), are jointly determined with credit spreads. Therefore, the explanatory power might be artificially inflated by using simultaneous explanatory variables. In particular, the option-implied risk measurements contain option-market risk premiums, which are expected to comove with the credit-market risk premiums, if the economywide risk aversion changes along with the business cycle. More careful controls are necessary to isolate the effects of objective risk measurements from those of subjective risk attitudes.

We first run the regressions with only the 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 as evidenced by the 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 effects, as predicted by the model in Section 2.

4.1 Summary statistics

Table 2 reports the sectoral and rating distributions of our sample companies as well as 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 (the combination of which accounts for 73 percent of the total). High-yield names (those in the categories double-B and lower) represent only 20 percent of total observations, an indication that CDSs on investment-grade names (those in the categories triple-B and higher) are still dominating the market.

Five-year CDS spreads, with a sample mean of 172 basis points, exhibit substantial cross-sectional differences and time variations. 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 (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 to 50 percent, regardless of whether historical or realized measures are used. The two volatility measures are also

[11]Throughout the remainder of this paper, "volatility" refers to the standard deviation term as distinguished from the variance representation.

highly correlated (the correlation coefficient is about 0.9). Concerning the jump measures, we detect significant jumps in about 16 percent of the transaction days. In those days when significant jumps have been detected, the jump component contributes 52.3 percent of the total realized variance on average (the range is about 40-80 percent 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 – that jumps on financial markets are rare and large.

Like CDS spreads, our volatility and jump measures 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 distinctions within the investment-grade categories are less obvious. As for jump measures, high quality 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 historical kurtosis. This finding looks surprising at first, as both skewness and kurtosis have been proposed as proxies for jump risk in previous studies.[12] On closer examination, however, the finding appears to 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 not informative at all. However, jump volatility, RV(J), and kurtosis are direct indicators of the existence of jumps in the continuous-time framework, but the non-negativity of both measures suggests that they are not able to reflect the direction of jumps; this ability is crucial in determining the pricing effects of jumps on CDS spreads.[13] Given the caveats of these measures, we choose to include the jump intensity, jump mean, and jump volatility measures as defined in equations (16) through (18). These measures combined can provide a full picture of the underlying jump risk.

4.2 Effects of volatility and jump on credit spreads

Table 4 reports the main findings of OLS regressions, which explain credit spreads solely with measures of equity-return volatility, measures of equity-return jump, or a combination

[12]Skewness is often loosely associated with the existence of jumps in the financial industry, whereas kurtosis can be formalized as an econometric test of the jump diffusion process (Drost, Nijman, and Werker, 1998).

[13]We have also calculated skewness and kurtosis on the basis of five-minute returns. The results are similar and therefore are not reported in this paper. More important, high-frequency measures, by definition, are unable to get rid of the shortcomings noted here.

of these measures. Regression (1), using one-year historical volatility alone, yields an R^2 of 45 percent, which is higher than the main result of Campbell and Taksler (2003; see Table II, regression 8, R^2 of 41 percent) with all volatility, ratings, accounting information, and macro-finance variables combined. Regressions (2) and (3) show that short-run realized volatility also explains a significant portion of spread variation and that combined long-run (one-year HV) and short-run (one-month RV) volatilities give the best R^2 result at 50 percent. The signs of coefficients are all correct—high volatility raises credit spread, and the magnitudes are all sensible: A volatility shock of 1 percentage point raises the credit spread 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 found here may be partly due to the gains from using CDS spreads rather than bond spreads, as 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; such inclusion is consistent with the theoretical prediction that equity volatility affects credit spreads through two factors (hypothesis 1). The existing literature usually adopts the long-run equity volatility, making the implicit assumption that equity volatility is constant over time. However, viewed from the theoretical perspective, this assumption is problematic. Note, for instance, that within the framework of Merton (1974), 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 volatilities 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 historical kurtosis, which also has a correct sign (more jumps increase spreads). This result is in contrast to the counterintuitive finding that skewness has a significantly positive effect on credit spreads (Cremers, Driessen, Maenhout, and Weinbaum, 2004b), perhaps, because their option-implied skewness measure has embedded a time-varying risk premium. However, the total predictability of traditional jump measures is still very dismal, as indicated by an R^2 of only 3 percent. In contrast, our new measures of jumps—regressions (5) to (7)—give significant estimates and by themselves explain 19 percent of credit spread variation. A few points are worth mentioning. First, jump volatility has the strongest effect, raising default spread 2.5 to 4.5 basis points for each increase of 1 percentage point. Second, when the jump mean effect (-0.2 basis point) is decomposed into positive and negative parts, the decomposition is somewhat asymmetric: positive jumps reduce spreads only 0.6 basis point, but negative jumps can increase spreads 1.6 basis points. Hence, we treat the two directions of jumps separately in the remainder of this paper. Third, average jump size has only a muted effect (-0.2), and jump intensity can switch sign (from 0.55 to -0.97), a result that may be explained by controlling for positive or negative jumps.

Our new benchmark regression (8) explains 54 percent of credit spread variation with volatility and jump variables alone, a striking result compared with the findings in previous studies. The effects 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 includes only long-run equity volatility, can be attributed to two causes. First, the decomposition of volatility into continuous and jump components, such that the time variation in equity volatility and the different aspects of jump risk are recognized, enables us to examine the different effects of those variables in determining credit spreads, as laid out in hypotheses (1) through (4). Second, as shown in a recent study by Andersen, Bollerslev, and Diebold (2005), using lagged realized volatility and jump measures of different time horizons can significantly improve the accuracy of the volatility forecast. Because the expected volatility and jump measures, which tend to be more relevant in determining credit spreads on the basis of structural models, are unobservable, empirical exercises typically have to rely on historical observations. Therefore, the gains in explanatory power may indicate that the forecasting ability of our set of volatility and jump measures is superior to that of 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).

In the first exercise, we examine the explanatory power of equity volatilities and jumps in addition to that of 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 percent of the variation in credit spreads, about the same percentage as volatility and jump effects are able to explain (see Table 4). In comparing the rating dummy coefficients, we find that low-rating entities apparently are priced significantly higher than are high-rating ones, a result that is economically intuitive and consistent with the existing literature. By adding volatility and jump risk measures, we can explain another 18 percent of the variation (R^2 increases to 74 percent). All volatility and jump variables have the correct signs and are statistically very significant. More remarkably, the coefficients are more or less of the same magnitude as in the regression without rating information except that the long-term historical volatility has a smaller effect.

The increase in R^2 is also large in the second pair of regressions. Regression (3) shows that the combination of 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, explains an additional 7 percent of credit spread movements on top of the percentage explained by rating information (regression (3) versus regression (1)). The increase from the combined effect (7 percent) is smaller than that from the volatility and jump effects (18 percent). Moreover, regression (4) suggests that the inclusion of volatility and jump effects provides another 14 percent of explanatory power compared with percentage explained by regression (3). R^2 increases to a very high level of 0.77. The results suggest that the volatility effect is different from the effects of other structural or macro factors.

Overall, the jump and volatility effects are very robust; the variables have the same signs, and the magnitudes of the coefficients are little changed. 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 one-year historical volatility and the one-month realized volatility (continuous component) are 18.57 percent and 25.85 percent respectively. Such shocks lead to a widening of the credit spreads by about 50 and 40 basis points respectively (multiply one standard deviation shock in Table 3 by corresponding regression coefficient in Table 5). For the jump component, a shock of one standard deviation in JI, JV, JP and JN (41.0 percent, 16.5 percent, 92.9 percent and 93.4 percent) changes the credit spread by about 36, 26, 59, and 34 basis points respectively. Altogether these factors could explain a large component of the cross-sectional difference and temporal variation in credit spreads observed in the data.

Returning to Table 5, we see from the full model of regression (4) that the macro-financial factors and firm variables have the expected signs. The market return has a significantly negative effect on spreads, but the market volatility has a significantly positive effect; these result are consistent with the business cycle effect. Because high profitability (ROE) implies an upward movement in asset value and a lower probability of default, it has a negative effect on credit spreads. A high leverage ratio is linked to a shift in the default boundary – which indicates that a firm is more likely to default – while a high dividend payout ratio leads to a reduction in a firm's asset value; therefore, both ratios have positive effects 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 variables have significantly positive effects, an indication that that the market is likely to connect the changes in these variables with a change in the stance of monetary policy (see the last two items in Table 1).

Another observation that 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 high. This result is consistent with the rating agencies' practice of rating entities according to their accounting information and probably according to macroeconomic conditions as well.

4.4 Robustness check

We check for robustness 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 of these two differ little. 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 effects on credit spreads, except that firm profitability (ROE) and recovery rate become insignificant. Also of interest is that the R^2 can be as high as 87 percent in the fixed-effect panel regression if we allow firm-specific dummies.[14]

We also run the same regression using one-year CDS spreads, also provided by Markit.[15] All the structural factors, particularly the volatility and jump factors, affected credit spreads as observed previously and the results showed the same signs and similar magnitudes. Interestingly, the explanatory power of those structural factors regarding short-maturity CDS

[14]We have also experimented with the heteroscedasticity and autocorrelation (HAC) robust standard error (Newey and West, 1987), which only makes the t-ratios slightly smaller but makes no qualitative differences. This result 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.

spreads is close to that of the benchmark case (regression (4) in Table 5). This result is in contrast to the finding in the existing literature that structural models are less successful in explaining short-maturity credit spreads. This improvement can be largely attributed to the inclusion of a jump process proxied by our jump measures; such inclusion allows the firm's asset value to change substantially over a short period.

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 either that the coefficients are largely dependent on firms' fundamentals (asset-value process, leverage ratio, and so on), or that the relationship can be nonlinear (Section 2.3). In the next two subsections, we address these two issues – that is, whether the effects of structural factors are intimately related to firms' credit standing and accounting fundamentals and whether the effects are 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, a result consistent with the finding in Huang and Huang (2003). Nevertheless, structural factors explain 41 percent and 54 percent of the credit spread movements in the two investment-grade groups, percentages that are much higher than those found by Huang and Huang (2003) (below 20 percent and around 30 percent respectively).

The regression results show that the coefficients of the volatility and jump effects for high-yield entities are typically several times larger than those for the top investment-grade names and those for triple-B name. To be more precise, for long-run volatility, the coefficients for the high-yield group and the top investment grade are 3.25 versus 0.75; for short-run volatility, 2.17 versus 0.36; for jump intensity, 1.52 versus 0.24; for jump volatility, 3.55 versus -0.03 (insignificant); for positive jump, -1.10 versus -0.13; and for negative jump, 0.52 versus 0.13. Similarly, the t-ratios of those coefficients in the high-yield group are much larger than those in the top investment grade. If we also take into account that high-yield names are associated with much higher volatility and jump risk (as measured by standard deviations in Table 3 and Figure 4), the economic implication of the interactive effect is even more pronounced.

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 larger effects (both statistically and economically) on credit spreads in the high-yield group. Those results reinforce the idea that the effects of structural factors, including volatility and jump risks, depend on the firms' credit ratings and fundamentals.

4.6 The nonlinear effect

Although 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 run a regression that includes the squared and cubic terms of volatility and jump variables (Table 8).

The regression finds strong nonlinearity in the effects of long-run and short-run volatility, jump volatility, and positive and negative jumps, results that are 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 the squared term and the cubic terms turn out to be statistically insignificant.

Given that the economic implications of the coefficients in our results are not directly interpretable, an illustration of the potential impacts of the nonlinear effects is useful (Figure 5). The lines plot the pricing effect of one-year and one-month volatilities, one-year jump intensity, one-year jump volatility, and one-year positive and negative jumps; each variable of interest ranges from the 5th- to the 95th-percentile of its distribution. Compared with the calibration exercise as plotted in Figure 3, the regression result is quite striking, as it fits remarkably well with the model predictions. Both the volatility measures and the jump measures have convex, nonlinear effects on credit spreads. The jump mean has an asymmetric effect, as negative jumps have larger pricing implications. The only difference between calibration exercise and the regression result lies in the effects of positive jumps, which increase credit spreads in the calibration but have opposite effects in the regression. However, the positive relationship between credit spreads and positive jumps in the calibration may be due to the particular drift specification used in the example and is more likely to be ambiguous from a theoretical perspective (Table 1).

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

We use an example in Huang and Huang (2003), in which the authors use the average equity volatility within a rating class in their calibration exercise, and they find that the predicted credit spread is much lower than the observed value (the average credit spread in the rating class). The underfitting of structural model predictions is also known as the credit premium puzzle. Nevertheless, this “averaging” of individual equity volatility can be problematic if its true effect 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, we find that the averaging of one-year historical volatility can cause an underprediction of credit spreads by 13 basis points.[16] Similarly, the averaging of one-month realized volatility, jump volatility, and negative jumps will cause the calibrated value to be lower by 12, 3, and 4.5 basis points respectively. In 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, an amount that is nontrivial given that the overall average CDS spread is just 172 basis points. Even though this nonlinear effect is not the only explanation for Huang and Huang’s finding (2003) and may not be able to fully resolve the credit premium puzzle, it can perhaps point us in a promising direction for future research to address this issue.

5 Conclusions

In this paper, we have extensively investigated the effects 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 effects, which predicts an extra 14-18 percent 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 significant than the rating dummy variables. These effects are economically significant and remain robust to the cross-sectional controls of fixed effect and random effect, an indication that the temporal variations of credit spreads are adequately explained by the lagged structural ex-

[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, $E(\cdot)$ refers to expectation operator or sample averaging, and Ω refers to other structural factors and parameters.

planatory variables. The volatility and jump effects are strongest for high-yield entities and financially stressed firms. Furthermore, these estimated effects exhibit strong nonlinearity, a result that is consistent with the implications from a structural model that incorporates stochastic volatility and jumps.

We adopted an innovative approach to identify the realized jumps of individual firms' equity, and this approach enabled us to directly assess the effects of various jump risk measures (intensity, variance, and negative jump) on the default risk premiums. These realized jump risk measures are statistically and economically significant, in contrast to the typical mixed findings in the literature that uses historical or implied skewness as jump proxies.[17]

Our study is only a first step toward improving our understanding of the effects of volatility and jumps on credit risk markets. Calibration exercises that take into account the time variation of volatility and jump risks and the nonlinear effects may 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 that incorporate time-varying volatility and jumps, are also worth more attention from research professionals.

[17]In a related paper, Tauchen and Zhou (2005) find that a realized jump volatility measure in equity market index has a superior forecasting power for credit spread indices than long-run and short-run volatilities, option-implied volatility, and other common risk factors like market return, SMB, and HML.

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 (2005), "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, 243–165.

Barndorff-Nielsen, Ole and Neil Shephard (2004), "Power and Bipower Variation with Stochastic Volatility and Jumps," *Journal of Financial Econometrics*, vol. 2, 1–48.

Bates, David S. (1996), "Jumps and Stochastic Volatility: Exchange Rate Process Implicit in Deutsche Mark Options," *The 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.

Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo (2005), "The Determinants of Credit Default Swap Premia," *Working Paper*, McGill University.

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, Bollerslev, and Diebold (2005); and Huang and Tauchen (2005) adopt test statistics of significant jumps on the basis of 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 intraday 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 ($j = 1$):

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

Following Andersen, Bollerslev, and Diebold (2005), 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. Using the Monte Carlo evidence in Huang and Tauchen (2005) and in Tauchen and Zhou (2005), we choose a significance level, α, of 0.999, with a one-lag 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 five-year CDS spreads and recovery rates for each entity in every month.

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

3. Realized measures of equity volatility and jump. The data are provided by TAQ (Trade and Quote), which includes intraday (tick-by-tick) transaction data for securities listed on the NYSE, AMEX, and NASDAQ. The following measures are calculated over the time horizons of one-month, three-month and one-year.

   - Realized volatility (RV): the volatility as defined by equation (12).
   - Jump intensity (JI): the frequency of business days with nonzero jumps, where jumps are detected on the basis of ratio statistics (equation (14)) with the test level of 0.999 (see Appendix A for implementation details).
   - Jump mean (JM) and jump variance (JS): the mean and the standard deviation of nonzero 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):

$$\begin{aligned}
\text{Leverage ratio (LEV)} &= \frac{\text{Current debt} + \text{Long-term debt}}{\text{Total equity} + \text{Current debt} + \text{Long-term debt}} \\
\text{Return on equity (ROE)} &= \frac{\text{Pretax income}}{\text{Total equity}} \\
\text{Dividend payout ratio (DIV)} &= \frac{\text{Dividend payout per share}}{\text{Equity price}}
\end{aligned}$$

5. Four macro-financial variables are collected from Bloomberg. They are the S&P 500 average daily return and the S&P 500 return volatility (in standard deviation terms) in the past six months, the average short-term rate (3-month Treasury rate) and the term spread (the slope of the yield curve, calculated as the difference between ten-year and three-month Treasury rates) in the previous month.

Table 1: **Theoretical predictions of the effects of structural factors on credit spreads**

Variables	**Effects**	**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	Ambiguous	Zhou (2001) suggests that credit spreads increase with 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, a second-order positive effect occurs 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 credit default swap (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.
Return on equity	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, Mithal, and Neis, 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 a rising inflation rate and a tightening of monetary policy.

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. CDS stands for credit default swap.

Sector	**Number**	**Percent**	**Rating**	**Number**	**Percent**
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 variable	**Mean**	**Std. dev.**	**Macro-financial variable**	**Mean** (%)	**Std. dev.**
Recovery rate (%)	39.50	4.63	S&P 500 return	-11.10	24.04
Return on equity (%)	4.50	6.82	S&P 500 volatility	21.96	4.62
Leverage ratio (%)	48.84	18.55	3-Month 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**

Here and in subsequent tables, (1) historical volatility, HV, realized volatility, RV, and the continuous and jump components of realized volatility, RV(C) and RV(J), are represented by their standard deviation terms; (2) the continuous and jump components of realized volatility are defined at a significance level of 0.999 (see Appendix A); (3) HS and HK refer to historical skewness and Kurtosis, and JI, JM, JV, JP, and JN refer, respectively, to jump intensity, jump mean, jump standard deviation, positive jump mean, and negative jump mean, as defined in Section 2; (4) negative jumps are defined in absolute terms.

3.A. Historical measures (%)

Variable	*1-month*		*3-month*		*1-year*	
	Mean	*Std. dev.*	*Mean*	*Std. dev.*	*Mean*	*Std. dev.*
Hist return	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 (%)

Variable	*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

Variable	*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*	
Variable	*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 JV	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

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

The numbers in parentheses are t-statistics.

	Dependent variable: 5-year CDS spread (basis points)							
Explanatory variable	**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
Observations	6342	6353	6337	6342	6328	6328	6328	6328

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

	1		2		3		4	
Explanatory variable	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*
Volatility & Jump								
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)
AA	36.85	(4.6)	-143.36	(18.2)	-81.66	(2.3)	-332.93	(11.3)
A	56.62	(15.9)	-126.81	(21.7)	-68.62	(2.0)	-320.11	(11.1)
BBB	142.06	(49.9)	-60.04	(9.4)	9.31	(0.3)	-258.11	(8.9)
BB	436.94	(73.4)	158.18	(18.1)	294.02	(8.4)	-46.14	(1.6)
B	744.95	(77.1)	376.90	(29.7)	556.58	(15.9)	127.03	(4.1)
CCC	1019.17	(34.9)	583.74	(22.1)	566.83	(9.9)	9.31	(0.2)
Macro-finance								
S&P 500 return					-1.21	(11.1)	-0.82	(8.9)
S&P 500 volatility					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)
Firm-specific								
Recovery rate					-2.65	(-5.4)	-0.59	(1.5)
Return on equity					-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	
Observations	6055		5950		4989		4952	

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

	Fixed effect				**Random effect**			
	1		**2**		**1**		**2**	
Explanatory variable	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*
Volatility & Jump								
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)
AA			-230.48	(7.8)			-393.30	(12.3)
A			-165.49	(7.2)			-330.47	(11.8)
BBB			-133.47	(6.5)			-281.13	(10.1)
BB			-110.64	(6.5)			-207.16	(7.1)
B							-62.38	(1.9)
CCC							-40.67	(0.4)
Macro-finance								
S&P 500 return			-0.80	(11.4)			-0.81	(11.5)
S&P 500 volatility			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)
Firm-specific								
Recovery rate			-0.13	(0.4)			-0.21	(0.6)
Return on equity			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		—		—	
Observations	6328		4952		6328		4952	

Table 7: **Regressions by rating groups**

	Group 1 (AAA, AA, and A)		**Group 2** (BBB)		**Group 3** (High-yield)	
Explanatory variable	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*	*Coef.*	*t-stat.*
Volatility & Jump						
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)
Macro-finance						
S&P 500 return	-0.41	(9.4)	-1.29	(11.4)	-1.69	(4.0)
S&P 500 volatility	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)
Firm-specific						
Recovery rate	0.61	(3.0)	1.11	(2.2)	-5.32	(3.8)
Return on equity	-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	
Observations	1881		2311		760	

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

Explanatory variable	*Coef.*	*t-stat.*
Volatility & Jump		
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)
AA	-128.08	(4.2)
A	-112.64	(3.8)
BBB	-49.84	(1.7)
BB	159.28	(5.2)
B	300.55	(9.7)
CCC	282.89	(5.8)
Macro-finance		
S&P 500 return	-0.97	(10.8)
S&P 500 volatility	2.04	(4.47)
3M Treasury rate	16.26	(4.9)
Term spread	40.48	(9.6)
Firm-specific		
Recovery rate	-0.44	(1.2)
Return on equity	-0.91	(3.9)
Leverage ratio	0.69	(8.2)
Div. payout ratio	18.22	(5.4)
Adjusted R^2	0.80	
Observations	4952	

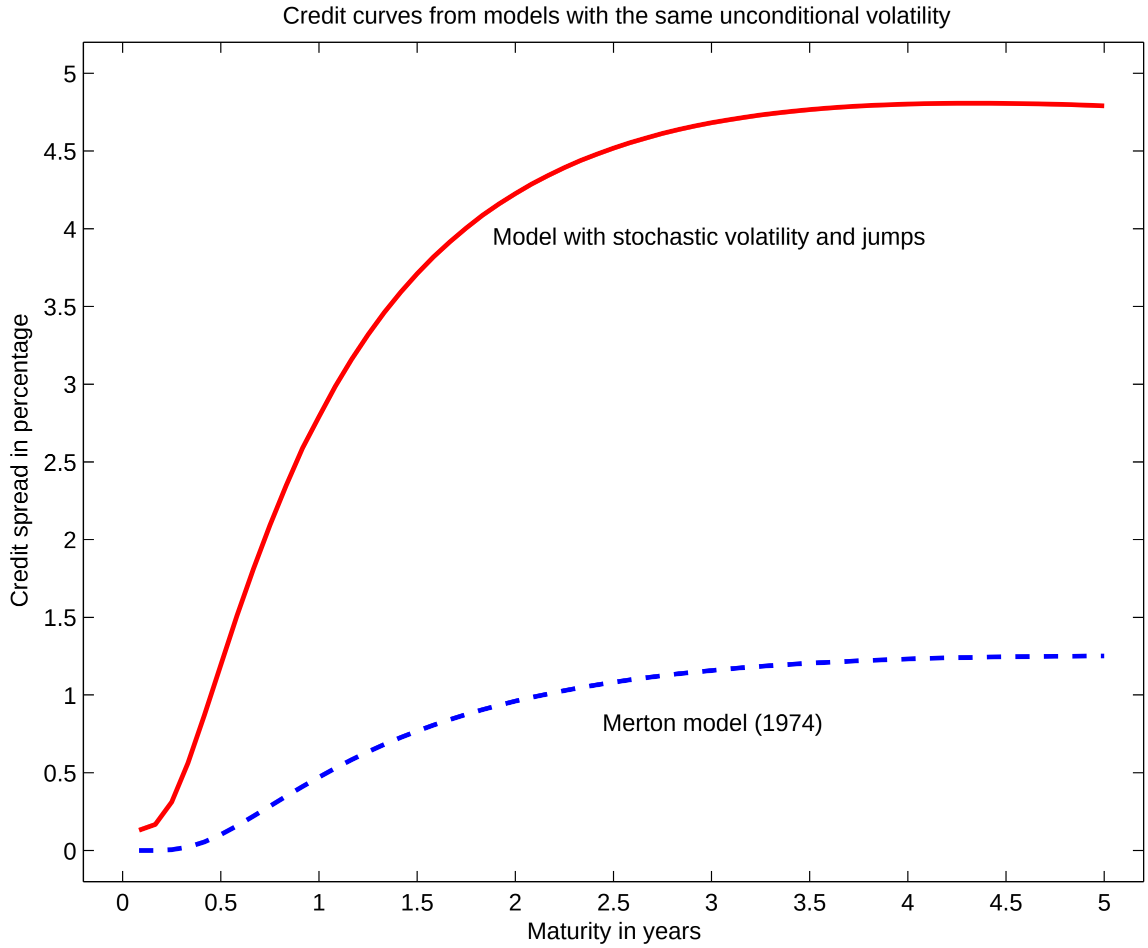

Figure 1: Credit yield curves

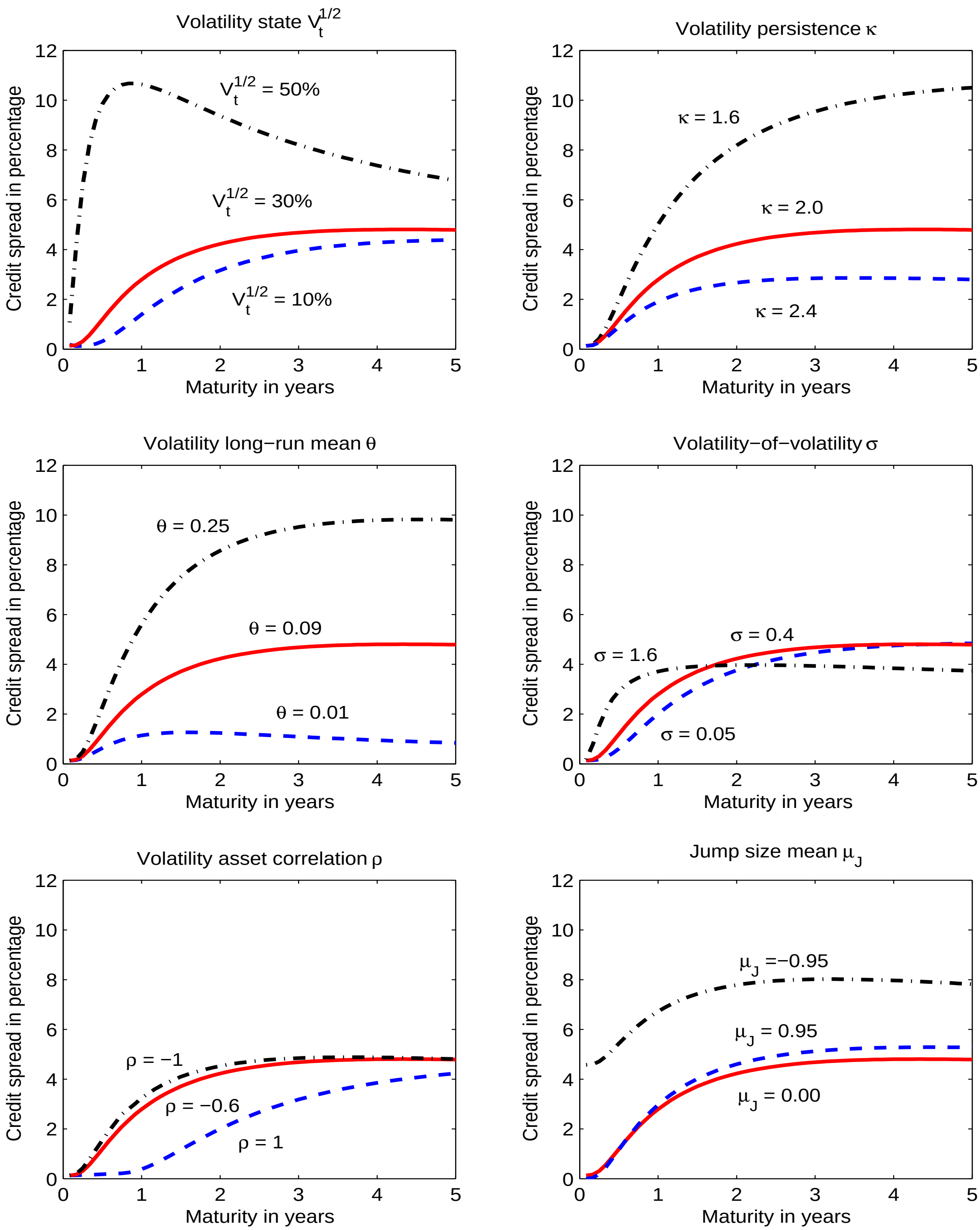

Figure 2: Comparative statics with volatility and jump parameters

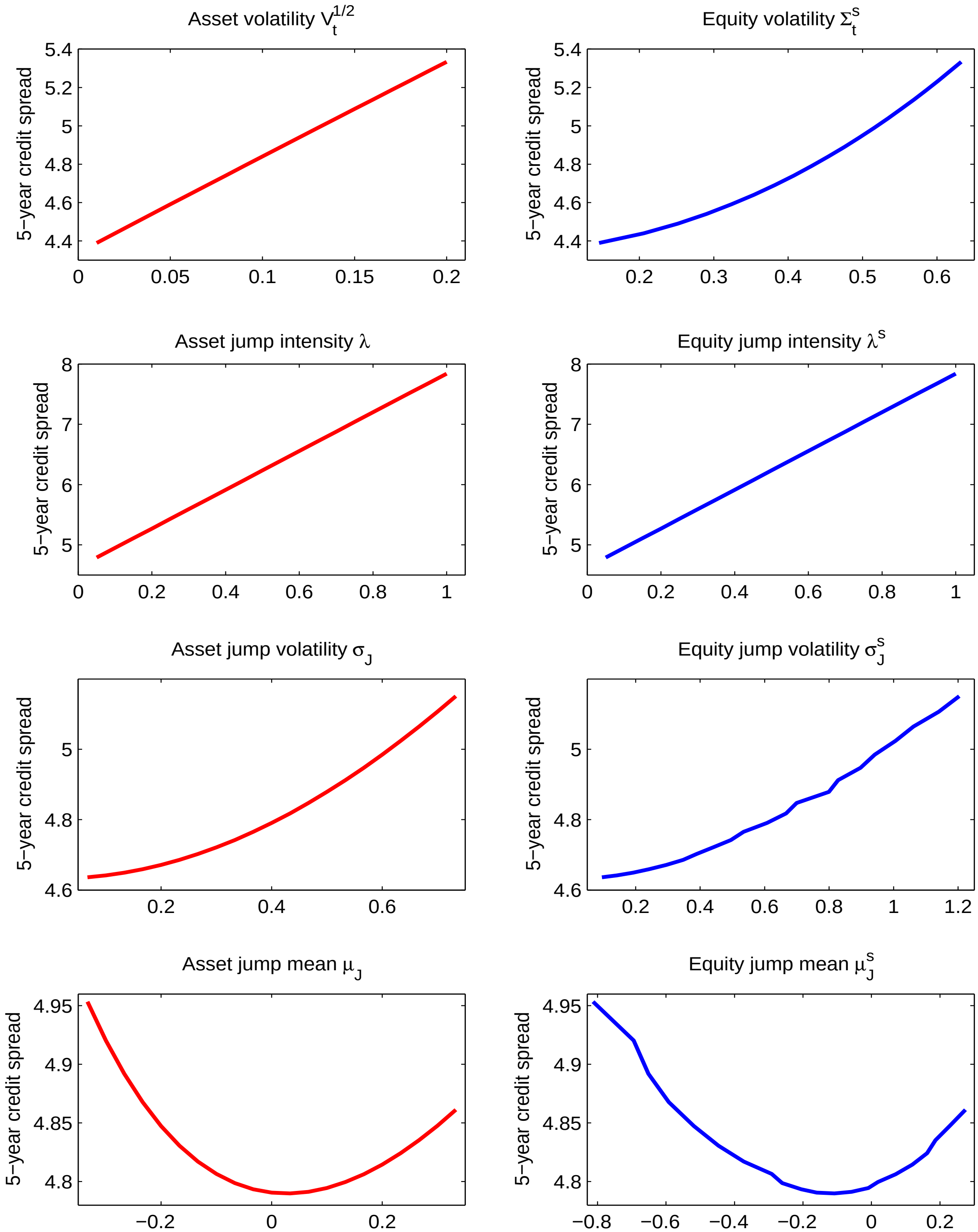

Figure 3: Linkages from asset and equity values to credit spreads

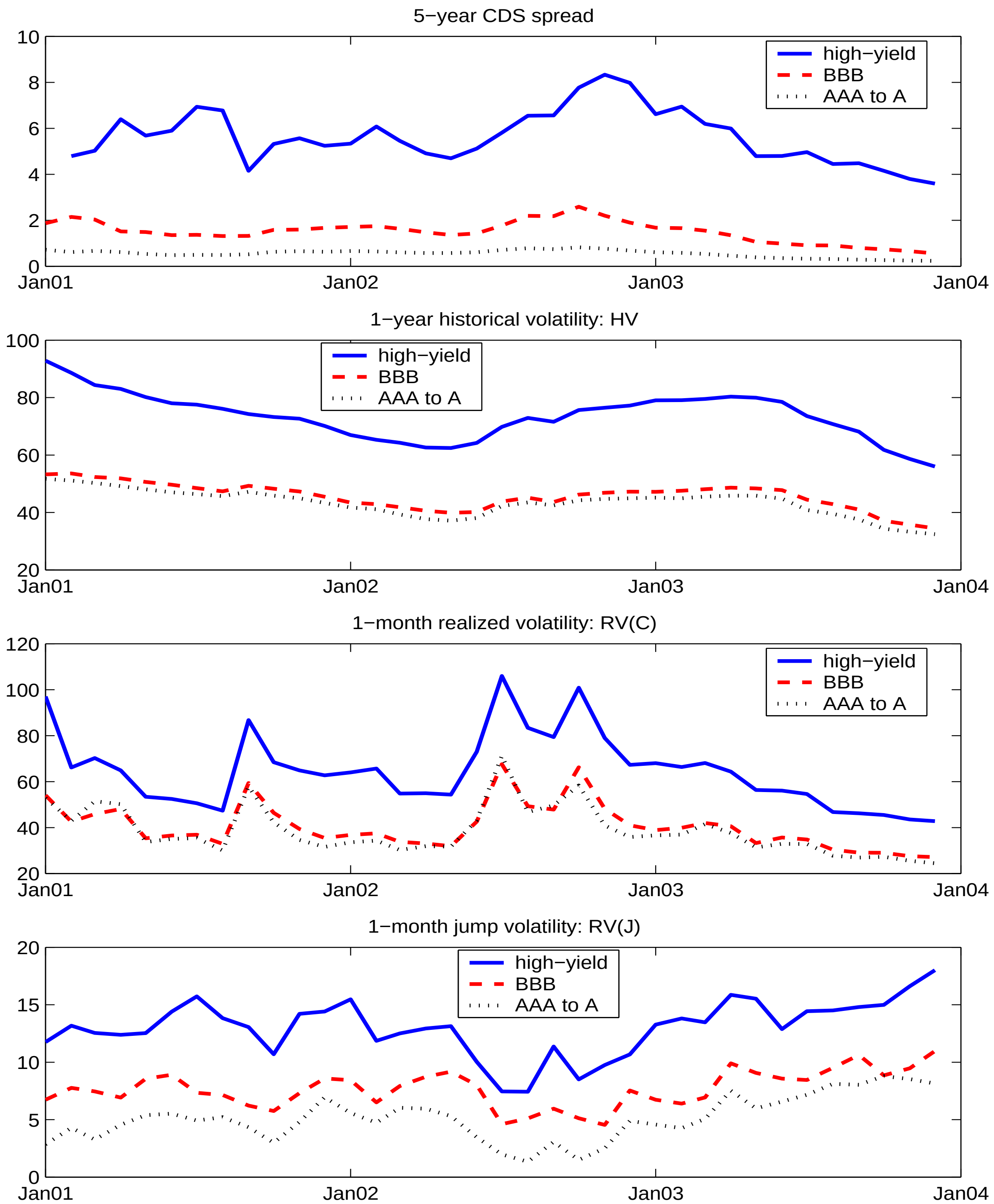

Figure 4: CDS spreads and volatility risks by rating groups

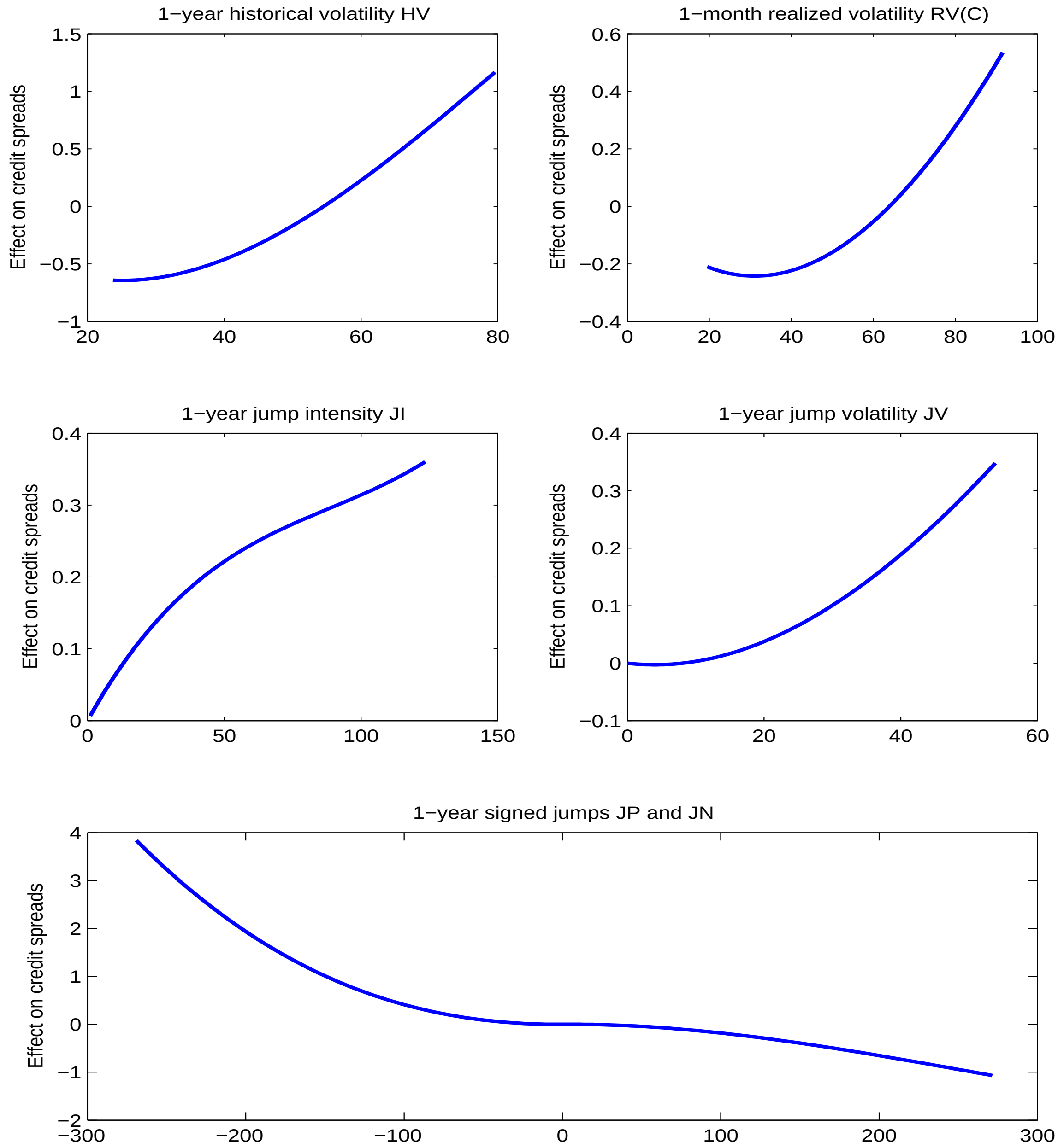

Figure 5: Nonlinear effects of volatility and jump

The illustration is based on the regression 1 in Table 8. X-axis variables have the value range of 5th and 95th percentiles.