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

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Abstract

This paper tries to explain the credit default swap (CDS) premium, using a novel approach to identify the volatility and jump risks of individual firms from high-frequency equity prices. Our empirical results suggest that the volatility risk alone predicts 50 percent of the variation in CDS spread levels, while the 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 jump risks on credit spreads are in line with the implications from a calibrated structural model with stochastic volatility and jumps, although the challenge of simultaneously matching credit spreads and default probabilities remains.

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

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Abstract

This paper tries to explain the credit default swap (CDS) premium, using a novel approach to identify the volatility and jump risks of individual firms from high-frequency equity prices. Our empirical results suggest that the volatility risk alone predicts 50 percent of the variation in CDS spread levels, while the 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 jump risks on credit spreads are in line with the implications from a calibrated structural model with stochastic volatility and jumps, although the challenge of simultaneously matching credit spreads and default probabilities remains.

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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 empirical approach for explaining credit spread variation, using volatility and jump risk measures constructed from high-frequency equity return data. We argue that these new measures may capture the effects of stochastic volatility and jumps in the underlying asset-value process (Huang and Huang, 2003; Huang, 2005) and that they may also enable structural variables to adequately explain credit spread variations, especially in the time-series dimension. In fact, the idea of explaining credit spreads via firm-level volatility or jump risks is not completely new. For instance, an 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. However, 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 (Delianedis and Geske, 2001; 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. In this paper, we provide important empirical evidence that carefully designed volatility and jump measures based on high-frequency data can significantly improve the forecasting power of temporal variations in credit spreads.

Our methodology builds on the recent literature on measuring volatility and jumps from high-frequency data. We adopt both historical (long-term time horizon) and realized (short-term time horizon) measures as proxies for the time variation in equity volatility, and we adopt realized jump measures as proxies for various aspects of the 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 do those 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 in financial prices 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 on jump days. These assumptions help us to identify the daily realized jumps of equity returns, as in Tauchen and Zhou (2006). From these realized jumps, we can estimate the jump intensity, jump mean, and jump volatility, and we can directly examine 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 depends on a direct measure of credit 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) and Chen, Lesmond, and Wei (2006b) 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 (2006) 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. The quicker response of CDS spreads may be partly due to the absence of funding and short-sale restrictions in the derivatives market. The fact that the CDS market leads the bond market in price discovery is integral to our improved explanation of the temporal changes in credit spread by default-risk factors.

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 the level of 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 that the R^2 increases to 77 percent. These results are robust to whether the fixed effect or the random effect is taken into account. 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. Equally important, both the volatility-risk and the jump-risk measures show strong nonlinear effects.

The positive results in the regression analysis suggest a promising way to improve the performance of structural models in the calibration exercise. 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 historical default probabilities simultaneously. In particular, we calibrate such a parametric structural model to the observed volatility and jump risk measures constructed from high-frequency equity returns, and we are able to match the empirical nonlinear effects of equity volatility and jump risk measures on credit spreads with the model-implied ones. Even the quantitative magnitudes of the calibrated sensitivity coefficients are close to the spread changes indicated by the regression-based findings. The only disagreement—on the positive jump effect—may be used as a specification diagnostic for this class of structural models, while its implementation in a full-blown econometric analysis is left for future research.

The remainder of the paper is organized into four sections. Section 2 introduces the methodology for disentangling volatility and jumps through the use of high-frequency data and briefly describes the CDS data and the structural explanatory variables. Section 3 presents the main empirical findings regarding the role of jump and volatility risks in explaining credit spreads. Section 4 calibrates a stylized structural model to match the nonlinear effects of volatility and jump risks on credit spreads. Section 5 is the conclusion.

2 Empirical method based on high-frequency data

Our main contribution is to use high-frequency equity return data to construct realized volatility and jump risk measures, which enables us to better capture the potential effects on credit spreads from time-varying volatility and jumps in the underlying asset return process. These realized measures, as demonstrated in our empirical analysis, are an improvement on the standard historical volatility measure and the implied skewness jump measure and can help explain the temporal variations in credit spreads. In addition, we use the credit default swap (CDS) spread as a direct measure of the credit risk premium, because this spread is less contaminated by the liquidity concerns raised by the corporate bond spread.

2.1 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. This assumption allows us to explicitly estimate the jump intensity, jump variance, and jump mean.

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:

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

where μ_t^s, σ_t^s, and J_t^s are, respectively, the drift, diffusion, and jump functions. W_t is a standard Brownian motion (or a vector of Brownian motions), dq_t is a Poisson process with intensity λ^s, 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:

$$r_{t,i}^s \equiv s_{t,i\cdot\Delta} - s_{t,(i-1)\cdot\Delta}, \tag{2}$$

where $r_{t,i}^s$ refers to the i^{th} within-day return on day t and Δ is the sampling frequency.[1]

[1] That is, $1/\Delta$ observations occur 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; Hansen and Lunde, 2006).

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:

$$\mathrm{RV}_t \equiv \sum_{i=1}^{1/\Delta} (r_{t,i}^s)^2 \to \int_{t-1}^{t} \sigma_s^2 ds + \sum_{i=1}^{1/\Delta} (J_{t,i}^s)^2, \tag{3}$$

$$\mathrm{BV}_t \equiv \frac{\pi}{2} \sum_{i=2}^{1/\Delta} |r_{t,i}^s| \cdot |r_{t,i-1}^s| \to \int_{t-1}^{t} \sigma_s^2 ds. \tag{4}$$

Therefore, the asymptotic difference between realized variance and realized 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:

$$\mathrm{RJ}_t \equiv \frac{\mathrm{RV}_t - \mathrm{BV}_t}{\mathrm{RV}_t}. \tag{5}$$

When appropriately scaled by its asymptotic variance, $z = \frac{\mathrm{RJ}_t}{\sqrt{\mathrm{Avar}(\mathrm{RJ}_t)}}$ converges to a standard normal distribution.[2] This test tells us whether a jump occurs during a particular day and how much jumps contribute 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, as noted earlier, 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:

$$J_t^s = \mathrm{sign}(r_t^s) \times \sqrt{\mathrm{RV}_t - \mathrm{BV}_t} \times \mathrm{I}(z > \Phi_\alpha^{-1}), \tag{6}$$

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

[2] 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.

parameters directly:

$$\hat{\lambda}^s = \frac{\text{Number of jump days}}{\text{Number of trading days}}, \tag{7}$$

$$\hat{\mu}_J^s = \text{Mean of } J_t^s, \tag{8}$$

$$\hat{\sigma}_J^s = \text{Standard deviation of } J_t^s. \tag{9}$$

Tauchen and Zhou (2006) 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 reexamine the effect of jumps on credit spreads.

2.2 Data description

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 predefined 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 the CDS spread. By definition, credit spread provides a pure measure of the default risk of the reference entity.[3]

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. Together with the pricing information, the data set reports average recovery rates used by data contributors in pricing each CDS contract.[4]

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

[3] The literature reflects 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; Berndt, Douglas, Duffie, Ferguson, and Schranz, 2005) and the role of CDS spreads in forecasting future rating events (Hull, Predescu, and White, 2004; Norden and Weber, 2004), as well as the role of implied volatility in explaining the credit risk premium (Schaefer and Strebulaev, 2004; Pan and Singleton, 2005; Cao, Yu, and Zhong, 2006).

[4] The quoted recovery rates reflect market participants' consensus view on *expected* losses and can thus differ substantially from *realized* losses.

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 because they are the most popularly traded in the U.S. market.[5] 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 January 2001 and ends 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.[6] 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 remove those CDS spreads that are 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: historical volatility calculated from daily equity prices (based on the CRSP data set) and realized volatility calculated from intraday equity prices (based on the TAQ data set). We calculate the two volatility measures over different time horizons (one month, three months, 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 5) with a significance level of 0.999 (for implementation details, see Appendix A). After identifying daily jumps,

[5] 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.

[6] Although composite quotes are available on a daily basis, we choose a monthly data frequency for two 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 a 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.

we then calculate the average jump intensity, jump mean, and jump standard deviation in a month, a quarter, and a year. The realized volatility and jump measures are calculated from the five-minute transaction data of equity prices.[7]

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), all obtained from Compustat. And we use four macro-financial variables (from Bloomberg) as proxies for the overall state of the economy: (1) the S&P 500 average daily return (past six months), (2) the volatility of the S&P 500 return (past six months), (3) the average three-month Treasury rate, and (4) the slope of the yield curve (ten-year minus three-month rate).

3 Empirical evidence

In this section, we first briefly describe the attributes of our volatility and jump measures. A case study on Enron in 2001 illustrates that the volatility and jump measures based on high-frequency data reflect the changes in credit conditions in a timely manner. We then proceed to examine the role of the equity volatility and jump risks of individual firms in explaining their CDS spreads. The benchmark regression is an OLS test that pools together all valid observations:

$$\begin{aligned} \mathrm{CDS}_{i,t} &= c + b_v \cdot \mathrm{Volatilities}_{i,t-1} + b_j \cdot \mathrm{Jumps}_{i,t-1} \\ &\quad + b_r \cdot \mathrm{Ratings}_{i,t-1} + b_m \cdot \mathrm{Macro}_{i,t-1} + b_f \cdot \mathrm{Firm}_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{10}$$

where the explanatory variables are the vectors listed in Section 2.2 and detailed in Appendix B.[8]

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, are jointly determined with credit spreads. Therefore, the explanatory power might be artificially inflated

[7] Our data sample of 307 firms includes relatively well-known names with large market caps. The medium and 90th percentiles of transaction duration are 11 seconds and 69 seconds, and the average log ask/bid spread is 0.0053, much smaller than the 0.0228 obtained from a random sample of 250 firms examined by Hasbrouck (2005). Furthermore, the autocorrelations of five-minute returns in our sample are on average -0.066 with a standard deviation of 0.05, a marginal sign of the effect of bid/ask bounce. Therefore, our approach of using five-minute transaction data to calculate the realized volatility seems acceptable. In particular, as detailed in Appendix A, we use staggered returns in calculating the realized volatility (as in Huang and Tauchen, 2005) to break the possible correlation between adjacent returns.

[8] We use monthly data in the regressions for reasons described in footnote 6. We also experiment with weekly data, and results are quite robust. The results are not reported here but are available upon request.

by using simultaneous explanatory variables. In particular, the *implied* volatility and jump risk measures contain option-market risk premiums, which are expected to co-move with the credit-market risk premiums if the economywide risk aversion changes along with the business cycle (see, for example, Campbell and Cochrane, 1999, for such an economic model). 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. Finally, we test for the nonlinearity of the volatility and jump effects, and we quantify the potential implications for empirical studies.

3.1 Summary statistics

We report the sectoral and rating distributions of our sample companies as well as summary statistics of quarterly firm-specific accounting variables and monthly macro-financial variables (Table 2). 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 credit default swaps 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 (the top panel of Figure 1).

We turn to summary statistics of firm-level volatilities and jump measures, which are based on monthly observations that are used in the regression exercises (Table 3).[9] The average daily return volatility (annualized) is between 40 percent and 50 percent regardless of

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

whether historical or realized measures are used. The two volatility measures are also highly correlated (the correlation coefficient is about 0.9). Concerning the jump measures, we detect significant jumps on about 15 percent of the transaction days, and we find an approximately equal share of positive and negative jumps. On those days when significant jumps are 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 assumptions we have used in the identification process—that jumps in financial prices 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 1). 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.[10] 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 an insufficient indicator of jumps. For example, if upward and downward jumps are equally likely to occur, then skewness is never informative. 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 unable to reflect the direction of jumps; this ability is crucial in determining the pricing effects of jumps on CDS spreads.[11] Given the caveats of these measures, we choose to include the jump intensity, jump mean, and jump volatility measures defined in equations (7) through (9). These measures combined can provide a full picture of the underlying jump risk.

3.2 A case study of Enron

This subsection sheds some light on the economic meaning of the volatility and jump risk measures used in this paper. For each of the 307 entities, we calculate the time series of daily

[10] 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).

[11] 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.

realized volatilities (RVs) and daily jumps, and we examine their co-movements with equity returns. Overall, the average correlation of the RV series and equity returns (in absolute terms) is 53 percent, much higher than that of the one-year historical volatilities (13 percent). This finding suggests that daily RVs can capture the changes in underlying asset values in a more timely matter. In addition, the correlations between daily jumps and daily equity returns are all positive, averaging 17 percent.

Of the 307 entities, an interesting case is Enron, the only company that went into bankruptcy during our sample period. It provides a vivid illustration of how well our volatility and jump risk measures capture the rapid movements in market credit conditions. Figure 2 plots the time series of daily realized volatilities and daily jumps, together with equity prices, CDS spreads, and one-year historical volatilities for Enron during the period from January 1 to November 29, 2001. The daily realized volatility has an average of 77 percent, and significant jumps are detected on 55 percent of business days—both percentages are much higher than the averages in our whole sample. These data reflect the turbulent environment experienced by Enron during the period. The increasing volatility in the equity market appears to be accompanied by rising CDS spreads, although the changes do not necessarily synchronize with each other. Figure 2 also depicts five major credit events that occurred at Enron in 2001, along with the movements of equity prices, volatilities, and jumps:

1. Enron entered 2001 with a stock price of about $80 but saw it sliding down. On June 19, Jeffrey Skilling, the incumbent chief executive officer, issued a statement to the market in which he reiterated "strong confidence" in Enron's earnings guidance. The stock market rebounded slightly on the day (with an equity return of 3.3 percent). On the same day, daily RV increased substantially from 66 percent to 158 percent, and the largest positive jump was detected during the sample period.

2. On August 14, Skilling resigned unexpectedly, and Wall Street started questioning Enron's performance. The equity price dropped from $42.93 to $36.85 in two days. A negative jump was detected on the day, and daily RV increased from 29 percent in the previous day to 84 percent and 131 percent on August 14 and 15 respectively.

3. On October 16, Enron reported its first quarterly loss in more than four years and disclosed a $1.2 billion charge against shareholders' equity. During the next four business days, the equity price dropped from $33.84 to $20.65; daily RVs moved to a higher range of 85-210 percent; negative jumps were detected on three out of the four days.

4. On November 8, Enron announced that it would restate earnings from 1997 through 2001. Equity prices dropped from \$11.30 to \$8.63 during that week; daily RVs shot up to 262 percent, and three negative jumps were detected.

5. On November 28, credit-rating agencies downgraded Enron's bonds to junk status, and Enron temporarily suspended all payments before filing for Chapter 11 bankruptcy on December 2. Both the daily RV and the one-year historical volatility hiked up, jumping from 173 percent to 1027 percent and from 86 percent to 208 percent respectively.

Overall, the case study suggests that short-term volatility based on high-frequency data is superior to historical volatility in capturing the *current* changes in market conditions and that our jump risk measure does quite a good job in reflecting large, unexpected credit events in the market.

3.3 Effects of volatility and jump on credit spreads

The rest of this section examines the role of firm-level volatility and jump risks in determining CDS spreads and follows the framework defined in equation (10).[12] We start with the findings of OLS regressions that explain credit spreads with measures of equity-return volatility, with measures of equity-return jump, or with a combination of these measures (Table 4). Regression (1), using one-year historical volatility alone, yields an R^2 of 45 percent, a level higher than the main result of Campbell and Taksler (2003; see Table II, regression 8, R^2 of 41 percent), in which the regression used a combination of all volatility, rating, accounting information, and macro-financial variables. Regressions (2) and (3) show that short-run (one-month) RV also explains a significant portion of spread variation and that combined long-run (one-year) HV and short-run RV 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 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- and short-term equity volatilities. By

[12] Because the default probability is determined nonlinearly by underlying structural factors, the credit spread cannot be simply characterized as a unit-root process. Thus, we use the level of credit spreads as the dependent variable throughout the empirical exercise.

contrast, the existing literature usually adopts only the long-term equity volatility, making the implicit assumption that equity volatility is constant over time. However, this assumption could be problematic from both theoretical and empirical perspectives. 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 (discussed in Section 4), equity volatility is time varying because both the asset volatility and the asset value are time varying. From the empirical side, short-term equity volatility often deviates substantially from the long-run trend in response to changes in market conditions, as we have observed in the Enron case study. Therefore, a combination of both long- and short-run volatilities can 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 in Cremers, Driessen, Maenhout, and Weinbaum (2004b), in which skewness has a significantly positive effect on credit spreads, perhaps because their option-implied skewness measure has embedded a time-varying risk premium. However, the total predictive power 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 (JV) has a strong effect, raising default spread 2.5 to 4.5 basis points for each percentage point of increase. Second, when the jump mean (JM) effect is decomposed into positive and negative parts, the decomposition is somewhat asymmetric: Positive jumps (JP) reduce spreads 9 basis points, but negative jumps (JN) can increase spreads by as much as 25 basis points. Hence, we treat the two directions of jumps separately in the remainder of the regression analysis. Third, jump intensity (JI) can switch signs (from 1.4 to -2.4), depending on whether we control for positive or negative jumps.

Moreover, the combination of volatility and jump variables (regression 8) turns out to be able to explain 54 percent of credit spread variation, 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 realized 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. 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.

3.4 Extended regression with traditional controlling variables

We now 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 (see Table 4). In comparing the rating dummy coefficients in Table 5, we find that low-rating entities are apparently 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—consisting of 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 only by rating information (regression 3 versus regression 1).[13] 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 the percentage explained by regression (3). R^2 increases to a high level of 0.77. The results suggest that the volatility and jump effects are different from the effects of other structural or macro factors.

Overall, the jump and volatility effects are robust; the variables have the same signs as before, and the magnitudes of the coefficients are little changed. To measure the economic significance more precisely, we return 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 (based on regression 4 coefficients in Table 5). For the jump component, a shock of one standard deviation in JI (16.4 percent), JV (16.5 percent), JP (5.9 percent) and JN (5.9 percent) changes the credit spread by about 36, 26, 59, and 34 basis points respectively. Altogether, these factors can explain a large component of the cross-sectional difference and temporal variation in credit spreads observed in the data.

In 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 results 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 gives an unclear answer, our regression shows that both variables have significantly positive effects, an indication that the market is likely to connect changes in these variables with changes in the stance of monetary policy (see 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

[13] We use the historical volatility of the S&P 500 index returns as a measure of market volatility. Substituting it with the implied volatility (VIX index) does not change the results.

included. The t-ratios of ratings drop 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.

3.5 Robustness check

The above finding that our volatility and jump risk measures have strong predictive power on the level of CDS spreads is quite striking. In this subsection, we run alternative regressions for the purpose of robustness check. First, we replace the OLS regression with 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 for the two types of effects differ little. In particular, the slope coefficients of the individual volatility and jump variables are remarkably stable and qualitatively unchanged. Moreover, the majority of the macro-financial and firm-specific 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]

Second, we run the same regression using one-year CDS spreads, also provided by Markit.[15] All the structural factors, particularly the volatility and jump factors, affect credit spreads as observed previously, and the results show the same signs and similar magnitudes. Interestingly, the explanatory power of those structural factors regarding short-maturity CDS 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 various jump risk proxies, which can allow the firm's asset value to change substantially over a short period.

Moreover, we check whether our volatility and jump risk measures help to explain changes in individual firms' credit spreads. Contrary to the regressions in spread levels discussed earlier in the paper, Table 7 shows that the explanatory power of structural factors on credit

[14] We have also experimented with the heteroscedasticity and autocorrelation 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.

spread changes is much lower, which is consistent with previous findings in Collin-Dufresne, Goldstein, and Martin (2001) and Schaefer and Strebulaev (2004).[16] Nevertheless, an important message from the change study is that the inclusion of our volatility and jump risk measures can improve the regression results substantially. For one, the coefficients for these measures are all statistically significant with correct signs (Regression 2). In addition, the increase in R^2 implies that the volatility and jump risk measures appear to have incorporated extra credit risk information (on the top of macro-financial variables and firms' balance sheet information) of the underlying entities.

3.6 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 (see Section 4.3). 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.

We first examine whether the volatility and jump effects vary across rating groups. Table 8 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 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 the triple-B names. 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, 3.79 versus 0.61; for jump volatility, 3.55 versus -0.03 (insignificant); for positive jump, -17.44 versus -2.01; and for negative jump, 8.26 versus 2.04. Similarly, the t-ratios of the coefficients in the high-yield group are much

[16] We use levels of jump risk measures because the definition of jumps by itself reflects market changes. All explanatory variables are lagged to prevent simultaneity bias, a choice consistent with the regressions in spread levels. Nevertheless, replacing them with contemporaneous variables (as in Collin-Dufresne, Goldstein, and Martin, 2001) yields similar results.

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 1), 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 financial 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.

3.7 The nonlinear effect

The majority of empirical studies on the determinants of credit spreads, including our baseline regressions, adopt a simplified linear relationship. Nevertheless, the theory usually predicts a nonlinear relationship between credit spreads and equity volatilities and jumps (as will be discussed in detail in Section 4). To test for the quantitative effect of the nonlinear relationship, we run a regression that includes the squared and cubic terms of volatility and jump variables (Table 9).

The regression finds strong nonlinearity in the effects of long- and short-run volatility, jump volatility, and positive and negative jumps, results that are consistent with theoretical predictions (see Section 4). In addition, 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 possible consequences of the nonlinear effects is useful (Figure 3). The lines plot the pricing effects 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 falls in the range between the 5th and the 95th percentiles of its observed values. 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 existence of the nonlinear effect may have important implications for empirical studies. In particular, it suggests that the linear approximation can cause potential bias in calibration exercises or in the evaluation of structural models. Such bias can arise either from assuming a linear relationship between credit spreads and structural factors, or from using average values of risk factors to predict model-implied credit spreads in a representative-firm setting.

4 Calibration support from a structural model

Our empirical findings of strong effects on credit spreads from realized jump risk measures and time series of volatilities, as well as the nonlinear nature of these effects, point to a possible choice of structural model with stochastic asset volatility and jumps. This section provides some calibration evidence that such a structural model can match our empirical findings in Section 3 and that it has the potential to fit both credit spreads and default probabilities. Our approach will follow the spirit of structural models, which differ from "hybrid" models (see Madan and Unal, 2000; Das and Sundaram, 2004; Carr and Wu, 2005, among others).

4.1 A stylized model with stochastic volatility and jumps

Assume the same market environment as in Merton (1974), and one can introduce stochastic volatility and jumps, as suggested by Huang and Huang (2003), into the underlying firm-value process:

$$\frac{dA_t}{A_t} = (\mu - \delta - \lambda\mu_J)dt + \sqrt{V_t}dW_{1t} + J_t dq_t, \quad (11)$$

$$dV_t = \kappa(\theta - V_t)dt + \sigma\sqrt{V_t}dW_{2t}, \quad (12)$$

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 studied extensively in the equity-option pricing literature (see, for example, Bates, 1996; Bakshi, Cao, and Chen, 1997), and the structural credit risk model with stochastic volatility and Lévy jumps has been examined by Huang (2005).

To be suitable for pricing corporate debt, we adopt two key assumptions from Merton (1974): (1) Default occurs only at maturity with debt face value as default boundary and (2) when default occurs, there is no bankruptcy cost and the absolute priority rule prevails. Use the no-arbitrage solution method of Duffie, Pan, and Singleton (2000), and one can solve the equity price, S_t, as a European call option on firm asset A_t with maturity T:

$$S_t = A_t F_1^* - Be^{-r(T-t)} F_2^*, \tag{13}$$

where F_1^* and F_2^* are so-called risk-neutral probabilities.[17] Therefore, the debt value can be expressed as $D_t = A_t - S_t$, and its price is $P_t = D_t/B$, where B is the face value. The credit default spread is then given by

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

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

4.2 Model calibration and comparative statics

We calibrate a series of models—Merton (1974), jump-diffusion, stochastic volatility, and jump-diffusion stochastic volatility (JDSV). Appendix C gives the details of our calibration methodology. Following Huang and Huang (2003), we evaluate the calibration results on their ability to fit both the credit spreads in our data set and the historical default probabilities between 1920 and 1999 from Keenan, Hamilton, and Berthault (2000). One important departure of our calibration approach from Huang and Huang (2003) is that we target the observed equity volatility and jump risk measures that are readily available from the high-frequency return data rather than the historical default probability and/or loss experiences. Note that the historical default loss may not be very informative about the time-varying default risk of our current data sample from 2000 to 2003. Also the historical default probabilities are estimated from rare events and have large standard errors. Therefore, they may not be useful as calibration inputs but are still useful as calibration outputs for judging the model performance.

Our calibration results suggest that the adoption of the JDSV model can significantly improve the empirical performance of structural models. Consistent with the findings in

[17] Assume no-arbitrage, and one can specify the corresponding risk-neutral dynamics as

$$\frac{dA_t}{A_t} = (r - \delta - \lambda^* \mu_J^*)dt + \sqrt{V_t}dW_{1t}^* + J_t^* dq_t^*, \tag{14}$$

$$dV_t = \kappa^*(\theta^* - V_t)dt + \sigma\sqrt{V_t}dW_{2t}^*, \tag{15}$$

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 $\mu_J^* = \mu_J + \xi_J$. To simplify our calibration exercise, we further assume no dividend and a zero coupon bond. One can also solve three special cases—the diffusion model (Merton, 1974), the jump-diffusion model (Merton, 1976), and the stochastic volatility model (Heston, 1993).

Huang and Huang (2003), the Merton-type structural models, and extensions with either stochastic volatility or jumps, have difficulties in simultaneously matching the observed credit spreads and historical default probabilities. The five-year credit spread based on the Merton model is only 106 basis points, much lower than the sample average of 172 basis points (Figure 4, top panel). Adding stochastic volatility or jumps alone can increase the spreads to 127 or 112 basis points, still far short of the observed ones. Similarly for the historical default probability at a five-year horizon, all three structural models overshoot the historical average of 6.65 percent (Figure 4, bottom panel).[18] By contrast, the combination of stochastic volatility and jumps in the JDSV model is able to match the five-year credit spread very closely (170 basis points) and at the same time generates a model-implied default probability that is closer to the historical average than the Merton model and the jump-diffusion model.

Nevertheless, the JDSV model cannot completely resolve the credit premium puzzle. The predicted five-year default probability is still higher than the historical average (10.12 versus 6.65 percent), thereby implying that the credit spreads would have been underpredicted, as in Huang and Huang (2003), if the default probability had been exactly matched. Moreover, at the one-year horizon the performance of structural models looks rather bleak. While the observed credit spread stands at 157 basis points, the calibrated models range from 11 to 34 basis points, which are less than 22 percent of the observed level even for our favored JDSV model.[19]

The sensitivities of credit curves with respect to asset volatility and jump parameters have an intuitive pattern (Figure 5). The high-volatility state, $V_t^{1/2}$, increases credit spread dramatically at shorter maturities of less than one year, and the credit curve becomes inverted when the volatility level is high (40 percent). A high mean reversion of volatility, κ, reduces spread (less persistent), whereas a high long-run mean of volatility, θ, increases spread (more risky). The volatility-of-volatility, σ, has a positive effect on spread at short maturities, but the effects on the long end are muted and do not have uniform signs. The volatility-asset correlation, ρ, increases credit spread as it becomes more negative. Finally, the jump size mean, μ_J, seems to have non-monotonic and asymmetric effects on credit spread—that is, both positive and negative jump means elevate the credit spread, but negative jump means seem to raise the spread higher.[20] The additional flexibility introduced by the volatility and

[18] The Merton model (13.16 percent) and the jump-diffusion model (16.77 percent) are way over-fitting, while the stochastic volatility model (9.72 percent) shows some improvement but still overshoots.

[19] Recent literature has advocated countercyclical risk premia (see, for example, Campbell and Cochrane, 1999). However, the calibration evidence from Huang and Huang (2003) and Chen, Collin-Dufresne, and Goldstein (2006a) suggests that such a model may still have difficulties in matching the observed credit spreads.

[20] Because the risk premium parameters ξ_v, ξ_λ, and ξ_J enter the pricing equation additively with κ, λ, and

jump parameters are critical for such a model to be able to match empirically both the credit spreads and the default probabilities better relative to other candidate models (Figure 4).

4.3 Model-implied link between equity volatility and credit spread

The JDSV model (equations 11 through 16) of the firm asset-value process implies the following specification of equity price by applying the Itô Lemma:

$$\begin{aligned}\frac{dS_t}{S_t} &= \frac{1}{S_t}\mu_t(\cdot)dt + \frac{A_t}{S_t}\frac{\partial S_t}{\partial A_t}\sqrt{V_t}dW_{1t} + \frac{1}{S_t}\frac{\partial S_t}{\partial V_t}\sigma\sqrt{V_t}dW_{2t} \\ &\quad + \frac{1}{S_t}[S_t(A_t(1+J_t), V_t; \Omega) - S_t(A_t, V_t; \Omega)]dq_t, \end{aligned} \tag{17}$$

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,

$$\Sigma_t^s = \sqrt{\left(\frac{A_t}{S_t}\right)^2 \left(\frac{\partial S_t}{\partial A_t}\right)^2 V_t + \left(\frac{\sigma}{S_t}\right)^2 \left(\frac{\partial S_t}{\partial V_t}\right)^2 V_t + \frac{A_t}{S_t^2}\frac{\partial S_t}{\partial A_t}\frac{\partial S_t}{\partial V_t}\rho\sigma V_t}, \tag{18}$$

$$J_t^s = \log[S_t(A_t(1+J_t), V_t; \Omega)] - \log[S_t(A_t, V_t; \Omega)], \tag{19}$$

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 (18) 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 6). In the figure, the left column suggests that the credit spread would increase linearly with the levels of asset volatility ($V_t^{1/2}$) and asset 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 its calibrated benchmark (0.13 percent). More interestingly, the effect is nonlinear and asymmetric—the negative jump mean increases spread much more than does the positive jump mean. The reason is that the first-order effect of jump mean

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 spreads are similar to the effects reported in Zhou (2001) and are therefore omitted.

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 unobserved changes in structural asset volatility and asset jump parameters, the right column in Figure 6 plots credit spread changes as related to the observed *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 four 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. As with asset jump volatility, equity jump volatility (σ_J^s) has a 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), like asset jump mean, has a nonlinear, asymmetric effect on credit spread, but it is more negative than asset jump mean.[21] 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 6, are qualitatively robust to alternative settings of the structural parameters.

4.4 Matching model implications and empirical evidence

Comparing the empirical evidence regarding the nonlinear effects of equity volatility and jump risk measures on credit spreads (see Table 9 and Figure 3), we find that the implications from the calibrated model are largely confirmed (Figure 6), both qualitatively and quantitatively:

- Equity volatility increases credit spread in a nonlinear fashion. The top two panels of Figure 3 clearly show that one-year historical volatility, HV, and one-month realized volatility, RV(C), do affect credit spreads in a positive and convex pattern, which qualitatively matches the pattern in the top-right panel of Figure 6, our illustration of the calibration exercise. Also important is that the regression coefficients on HV and RV(C) are all statistically significant in the linear, quadratic, and cubic terms (Table 9).

- Equity jump intensity increases credit spread linearly. The evidence is inclusive along this line—although the middle-left panel in Figure 3 shows a concave positive relationship between equity jump intensity (JI) and credit spreads, the coefficient estimates

[21] 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 2,000 times and use equation (19) to numerically evaluate μ_J^s and σ_J^s.

on JI, JI^2, and JI^3 are all statistically insignificant (Table 9).[22]

- Equity jump volatility increases credit spread nonlinearly. There seems to be no disagreement on this convex positive relationship, as can be seen by comparing the middle-right panel of Figure 3 (empirical evidence) with the third right panel of Figure 6 (numerical evidence).

- Equity jump mean affects credit spread in a nonlinear, asymmetric way; negative jumps tend to have larger effects. The main finding of a nonlinear negative relationship between jump mean and credit spread (lower panel of Figure 3) is in line with the model implication (bottom-right panel of Figure 6). However, there is a clear disagreement—the calibrated model predicts that positive jump mean increases credit spread, while the regression result shows the opposite effect.[23]

Overall, the magnitudes of the credit spread sensitivities to volatility and jump risks, as implied by the model calibration exercise (Figure 6), are not much different from those implied by the extended regression results reported in Table 9 and illustrated in Figure 3. However, the issue of whether a structural model is rejected or not by empirical evidence can only be resolved in a full-blown econometric analysis, in which all aspects of model-data matching are appropriately taken into account by a well-designed estimation method, an objective for future research.

5 Conclusions

We have extensively investigated the effects of 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 predict an additional 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

[22]Conceptually, if jump intensity is a linear or nonlinear function of asset value or volatility, then credit spreads can be nonlinearly affected by jump intensity. Our empirical finding does not rule out this possibility. We thank the referee for pointing out this interpretation.

[23]Because our calibration exercise is robust to different parameter settings, this finding on the jump mean effect can be used as a model diagnostic about such a structural specification and its jump component in particular.

captured 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, a result that is consistent with the implications from a structural model that incorporates stochastic volatility and jumps.

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

Our study is only a first step toward improving our understanding of the effects of volatility and jumps in 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, also warrant more research.

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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 (5):

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

where Δ refers to the intraday sampling frequency, BV_t is the bipower variation defined by equation (4), 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), we define the continuous and jump components of realized volatility on each day 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 (3), $\mathrm{I}(\cdot)$ 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 (2006), we choose a significance level, α, of 0.999 and make a one-lag adjustment for microstructure noise.

B Data sources and definitions

The following variables are included in our study:

1. CDS data are 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 are calculated from the daily CRSP data set. Based on daily equity prices, we calculate average historical 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 are based on the five-minute transaction data provided by the TAQ (Trade and Quote) data set, which includes securities listed on the NYSE, AMEX, and NASDAQ. The following measures are calculated over the time horizons of one month, three months, and one year.

   - Realized volatility (RV): the volatility as defined by equation (3).
   - Jump intensity (JI): the frequency of business days with nonzero jumps, where jumps are detected on the basis of ratio statistics (equation 5) with the test level of 0.999 (see Appendix A for implementation details).
   - Jump mean (JM) and jump volatility (JV): 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 is obtained from Compustat on a quarterly basis. We use the last available quarterly observations 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 in the past six months, the S&P 500 return volatility (in standard deviation terms) in the past six months, the average short-term (three-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.

C Calibration Details of Structural Models

We calibrate four models—Merton (1974), jump-diffusion, stochastic volatility, and jump-diffusion stochastic volatility—to the observed equity volatility and jump measures constructed from high-frequency return data. Both credit spread (172 basis points at five-year horizon) and default probability (6.65 percent at five-year horizon) are used as outputs to judge model performance. Based on our data sample from 2000 to 2003, we make common parameter choices: risk-free rate 0.0218, equity return 0.0450, and leverage ratio 0.4884. For each model, the key parameters are either estimated or calibrated from our data sets.

1. **Merton (1974) Model:** Asset volatility is chosen as 0.28 such that the model-implied equity volatility matches the observed one: 0.4583.

2. **Jump-Diffusion Model:** Asset volatility 0.2817, jump intensity 0.1362, jump mean 0.0185, and jump volatility 0.1550. These choices match the observed equity volatility 0.4583, jump intensity 0.1362, jump mean 0.0013, and jump volatility 0.255.

3. **Stochastic Volatility Model:** Asset volatility dynamics is estimated by GMM as in Zhou (2003) and is rejected with a p value of less than 1 percent. The estimated parameters are mean reversion 0.8146, long-run mean 0.0549, volatility-of-volatility 0.1510. Asset-volatility correlation -0.3449 is estimated with book asset, and volatility risk premium -0.27 is calibrated to match the model-implied link between asset volatility and equity volatility.

4. **Jump-Diffusion Stochastic Volatility Model:** Asset volatility dynamics is estimated by GMM as in Zhou (2003) and is rejected with a p value of less than 1 percent. The estimated parameters are mean reversion 1.0025, long-run mean 0.0554, and volatility-of-volatility 0.1680. Asset-volatility correlation -0.3449 is estimated with book asset, and volatility risk premium -0.27 is calibrated to match the model-implied link between asset volatility and equity volatility excluding jumps. The asset jump parameters are calibrated as jump intensity 0.1362, jump mean 0.02, and jump volatility 0.16. These choices match the observed equity volatility 0.4420, jump intensity 0.1362, jump mean 0.0013, and jump volatility 0.255.

To solve these models, we adopt the simplifying assumptions regarding default and recovery: (1) default only occurs at maturity, (2) default barrier equals the face value, and (3) bankruptcy cost is 10 percent of remaining firm value. These assumptions are consistent with the existing literature in calibrating the Merton-type models with zero-coupon bonds (see, for instance, Collin-Dufresne and Goldstein, 2001).

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

Variable	**Effect**	**Economic intuition**
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 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 4.3).
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 and Schwartz, 1995). 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, 2001-2003

The upper-left panel reports the sectoral distribution of sample entities. The upper-right panel describes the rating distribution of credit spread observations. The lower panels report summary statistics of firm-specific and 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 staple	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
Dividend 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, 2001-2003

Here and in subsequent tables and figures, variables are abbreviated as in this note. The table reports summary statistics of firm-level historical volatility (HV), historical skewness (HS), historical kurtosis (HK), and realized volatility (RV), including a breakdown of realized volatility into its continuous (RV(C)) and jump (RV(J)) components. All volatility measures are represented by their standard deviation terms. The jump component of realized volatility is defined by the test statistics in Appendix A at a significance level of 0.999. JI, JM, JV, JP, and JN refer, respectively, to the jump intensity, jump mean, jump standard deviation, average positive jumps, and average negative jumps, as defined in Section 2. Note that 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 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 (%)

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

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*	
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	8.39	10.38	15.92	18.35	18.04	17.37
1-year JM	0.97	10.25	0.61	9.43	-1.97	19.64
1-year JV	20.63	12.39	24.51	13.50	35.60	22.81
1-year JP	4.05	3.29	6.29	5.07	9.92	8.10
1-year JN	3.89	3.28	5.77	4.67	10.29	8.37

Table 4 Baseline regressions

The table reports OLS regression results with five-year CDS spread as the dependent variable and firm-level equity volatility and jump measures as the explanatory variables. Numbers in parentheses are *t*-ratios.

	Dependent variable: 5-year CDS spread (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					1.38		-2.41	3.66
					(7.0)		(7.0)	(13.4)
1-year JM					-3.36			
					(14.9)			
1-year JV					4.52		2.51	1.32
					(28.2)		(10.3)	(7.2)
1-year JP						-7.13	-9.31	-9.92
						(7.3)	(8.2)	(11.7)
1-year JN						23.17	25.12	7.23
						(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 Extended regressions

The table reports the OLS regression results that explain five-year CDS spreads using firm-level volatility and jump measures, rating dummies, macro-financial variables, firm-specific variables, and recovery rates used by CDS price providers. Numbers in parentheses are t-ratios.

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			2.32	(10.3)			2.21	(9.4)
1-year JV			1.29	(8.9)			1.58	(11.0)
1-year JP			-10.87	(15.8)			-9.97	(14.8)
1-year JN			6.09	(8.6)			5.70	(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 volume					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)
Dividend 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: Panel data estimation

The regression adopts the panel data technique to examine the determinants of five-year CDS spreads. Explanatory variables are the same as in Table 5. Numbers in parentheses are t-ratios.

	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	0.53	(1.5)	0.38	(1.1)	1.07	(3.2)	0.86	(2.6)
1-year JV	1.06	(6.9)	1.35	(9.5)	1.01	(6.7)	1.35	(9.7)
1-year JP	-10.97	(14.6)	-8.77	(12.3)	-10.30	(14.0)	-8.44	(12.2)
1-year JN	7.22	(8.5)	5.34	(6.7)	8.53	(10.4)	6.78	(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 volume			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)
Dividend payout ratio			45.23	(9.1)			42.89	(8.9)
Adjusted R^2	0.81		0.87		–		–	
Observations	6328		4952		6328		4952	

Table 7 Determinants of CDS spread changes

The table reports the OLS regression results that explain monthly changes in five-year CDS spreads. Explanatory variables include (monthly) changes in macro-financial variables and firm-specific variables, changes in volatility measures, and levels of jump measures. All explanatory variables are lagged to avoid simultaneity bias.

	Regression 1		**Regression 2**	
	coef	*t-stat*	*coef*	*t-stat*
Constant	-1.67	(2.2)	-4.41	(3.3)
Changes in				
1-year return			-0.39	(9.4)
1-year HV			1.20	(5.3)
1-month RV(C)			0.39	(9.4)
Levels of				
1-year JI			0.17	(1.9)
1-year JV			0.22	(3.6)
1-year JP			-1.43	(5.1)
1-year JN			0.76	(2.8)
Changes in				
S&P 500 return	-0.52	(10.0)	-0.52	(10.0)
S&P 500 volume	2.92	(8.2)	1.05	(2.9)
Short rate	-19.12	(4.1)	-15.25	(3.3)
Term spread	-2.90	(1.0)	2.02	(0.7)
Changes in				
ROE	-0.13	(1.2)	-0.11	(1.1)
Leverage ratio	0.50	(2.7)	0.48	(2.7)
Dividend payout ratio	17.68	(9.0)	16.12	(8.5)
Adjusted R^2	0.07		0.14	
Observations	4774		4774	

Table 8 Regressions by rating groups

We run the same OLS regression as in Table 5, but we divide the sample into three groups based on rating information. Numbers in parentheses are t-ratios.

	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	0.61	(3.6)	0.75	(2.6)	3.79	(4.4)
1-year JV	-0.03	(0.3)	0.06	(0.2)	3.55	(9.4)
1-year JP	-2.01	(4.0)	-4.91	(5.6)	-17.44	(9.0)
1-year JN	2.04	(4.7)	9.48	(9.4)	8.26	(4.3)
S&P 500 return	-0.41	(9.4)	-1.29	(11.4)	-1.69	(4.0)
S&P 500 volume	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)
Dividend 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 9 Nonlinear effects of equity volatilities and jumps

The table examines the nonlinear effects of volatility and jump measures in explaining five-year CDS spreads. The nonlinear terms are rescaled to make their coefficients comparable. For instance, the squared and cubic terms of historical volatility (HV) are adjusted by a scale of $\sqrt{250}$—that is, $HV^2 \equiv HV \cdot HV/\sqrt{250}$ and $HV^3 \equiv HV \cdot HV \cdot HV/250$. The same adjustment is applied to RV(C), JV, JP, and JN (defined in Table 3). In contrast, JI is adjusted by a scale of 10.

Variable	*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	1.71	(1.5)
JI^2	-3.69	(1.2)
JI^3	3.46	(1.2)
JV	-0.14	(0.3)
JV^2	0.27	(3.1)
JV^3	-0.01	(2.8)
JP	0.34	(0.1)
JP^2	-9.23	(3.2)
JP^3	2.93	(2.7)
JN	0.35	(0.1)
JN^2	14.63	(4.8)
JN^3	-6.18	(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 volume	2.04	(4.47)
Short 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)
Dividend payout ratio	18.22	(5.4)
Adjusted R^2	0.80	
Observations	4952	

Figure 1 CDS spreads and volatility risks by rating groups

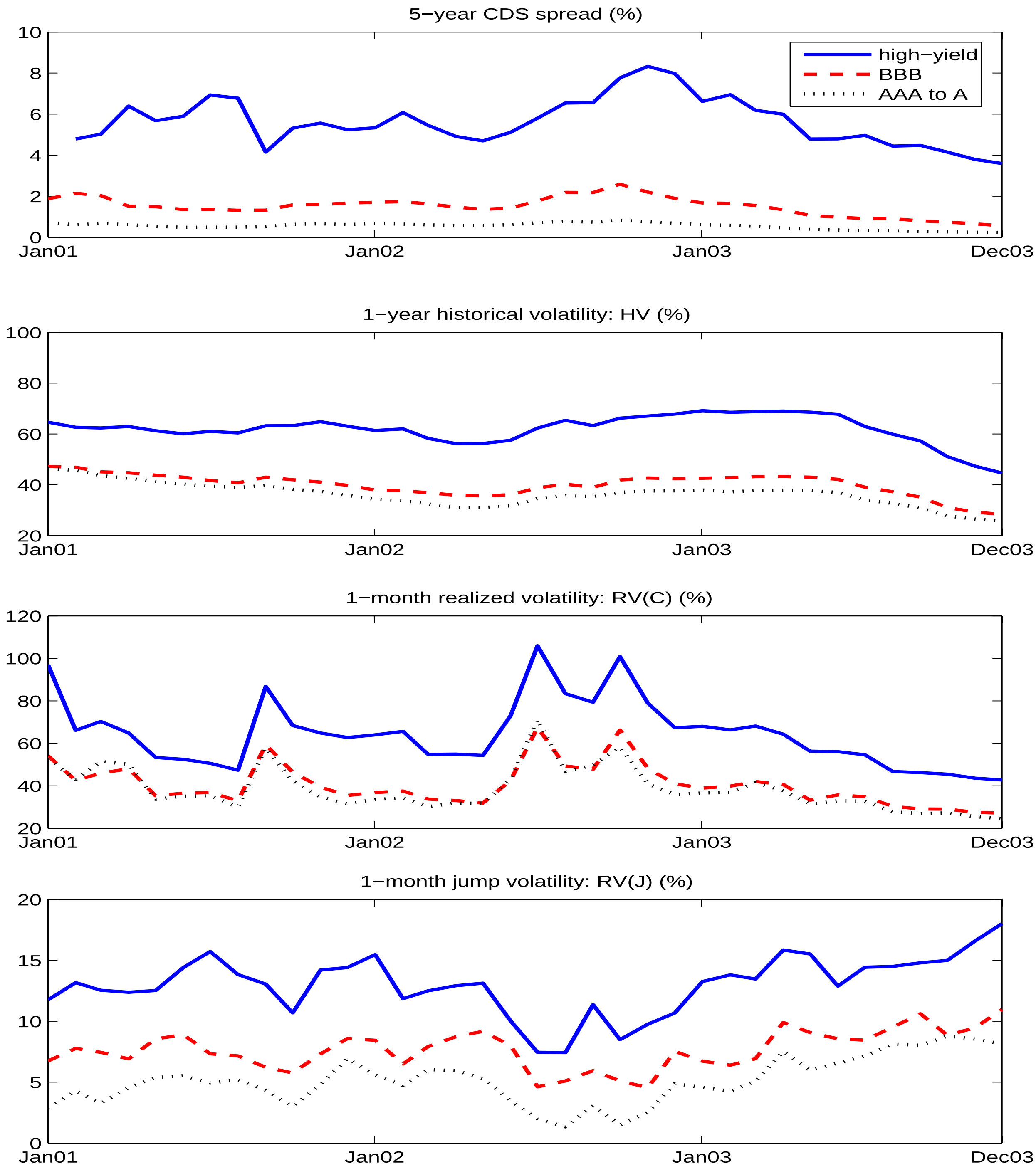


Figure 2 A case study on Enron

The figure covers the period from January 1 to November 29, 2001. Jumps are defined on a daily basis using the method described in Appendix A.

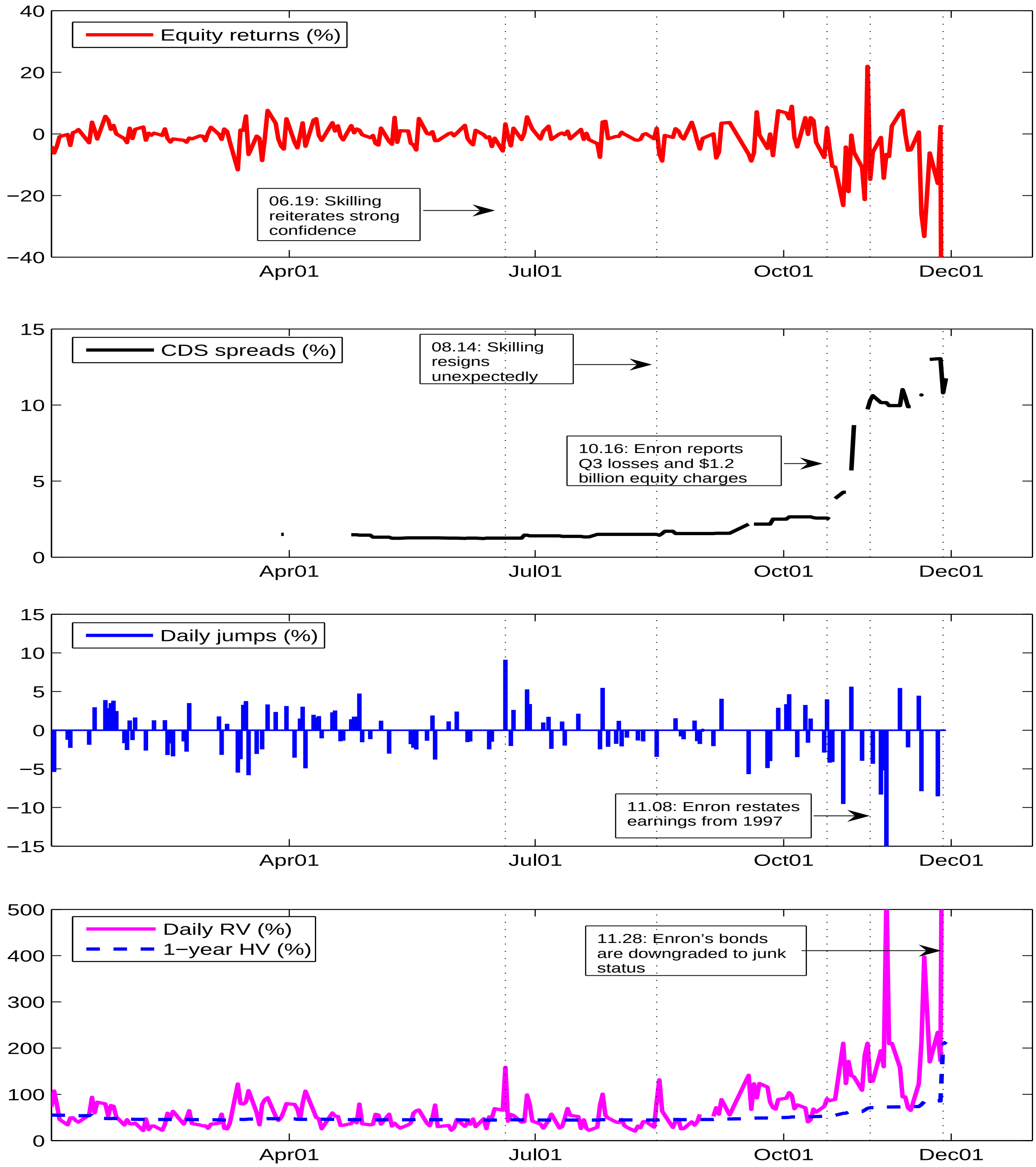


Figure 3 Nonlinear effects of volatility and jump variables

The illustration is based on regression (1) in Table 9. X-axis variables fall in the range between the 5th and 95th percentiles of the observed values.

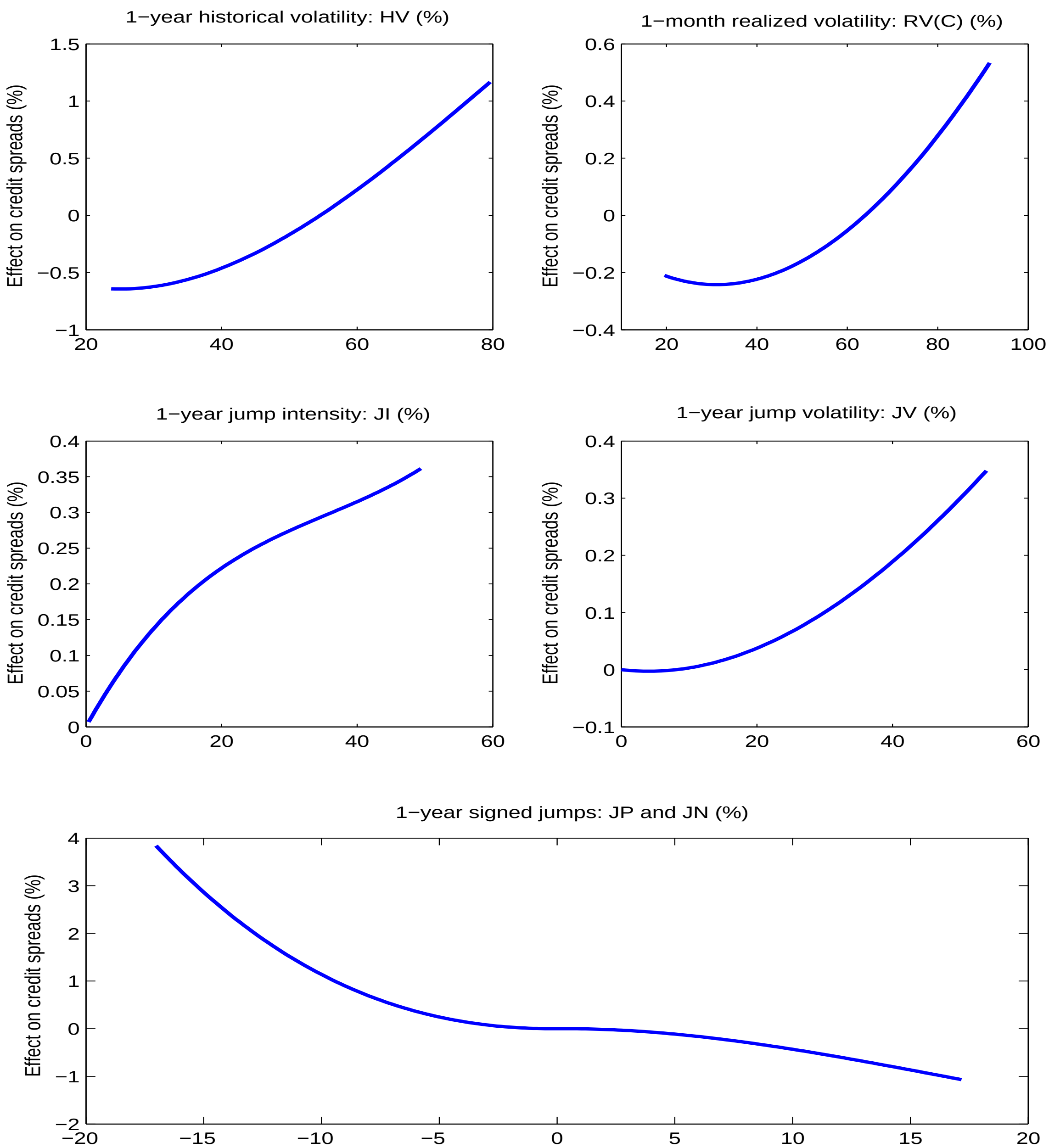
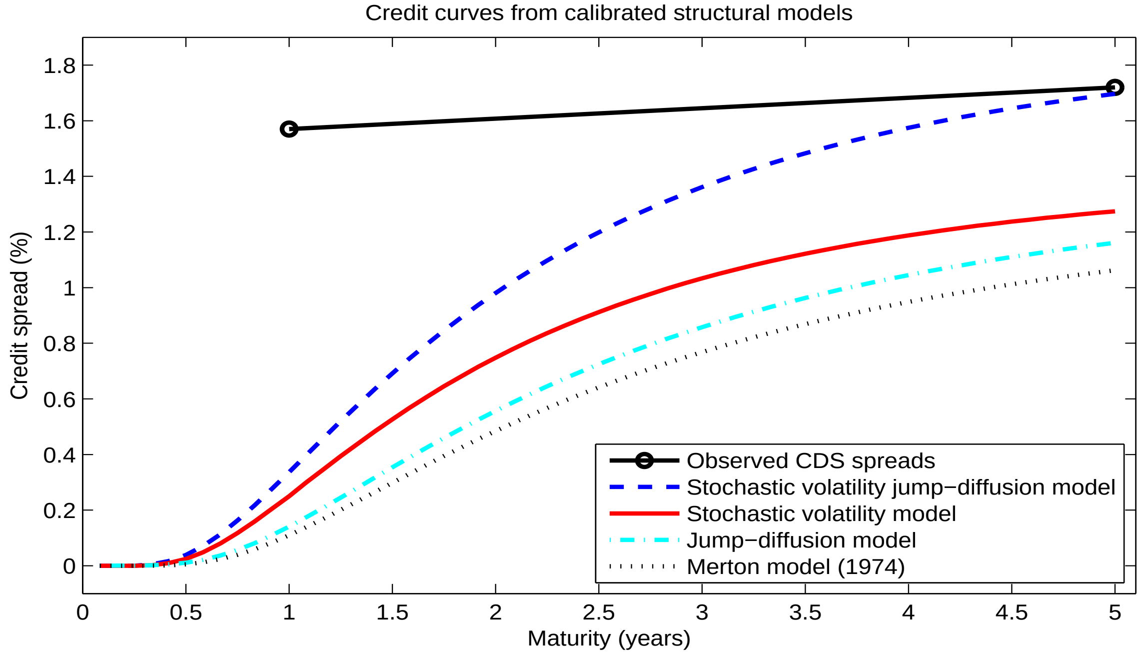


Figure 4 Credit spread curves and default probabilities



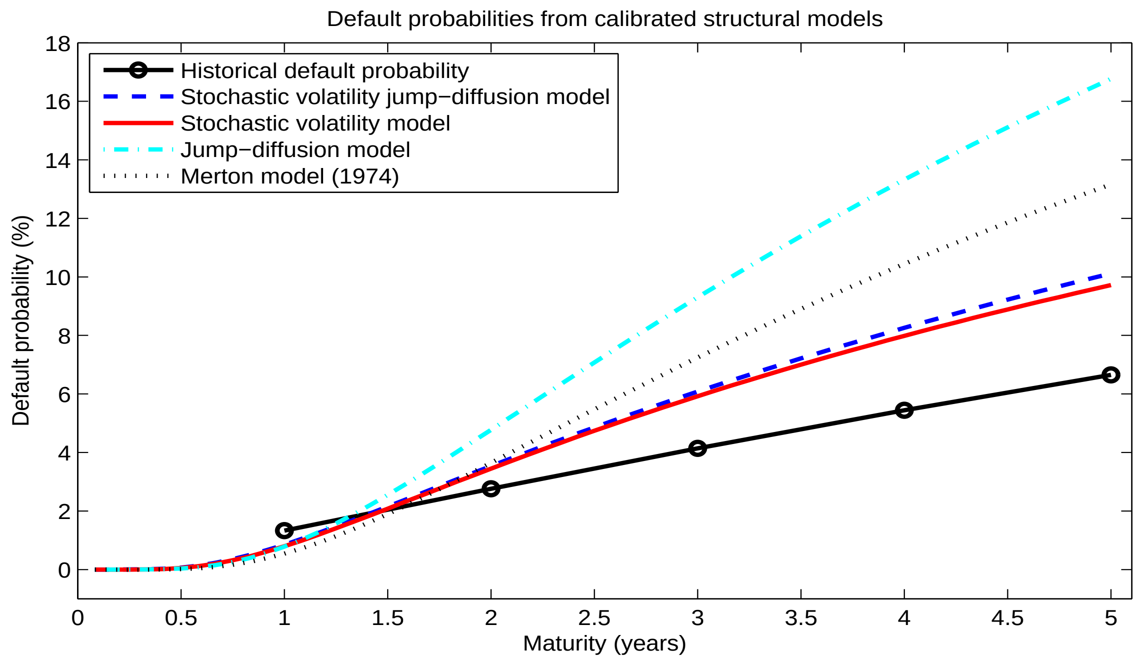


Figure 5 Comparative statics with volatility and jump parameters

The figure illustrates the sensitivity of credit spreads to the structural jump and volatility parameters of the underlying asset return and asset volatility processes.

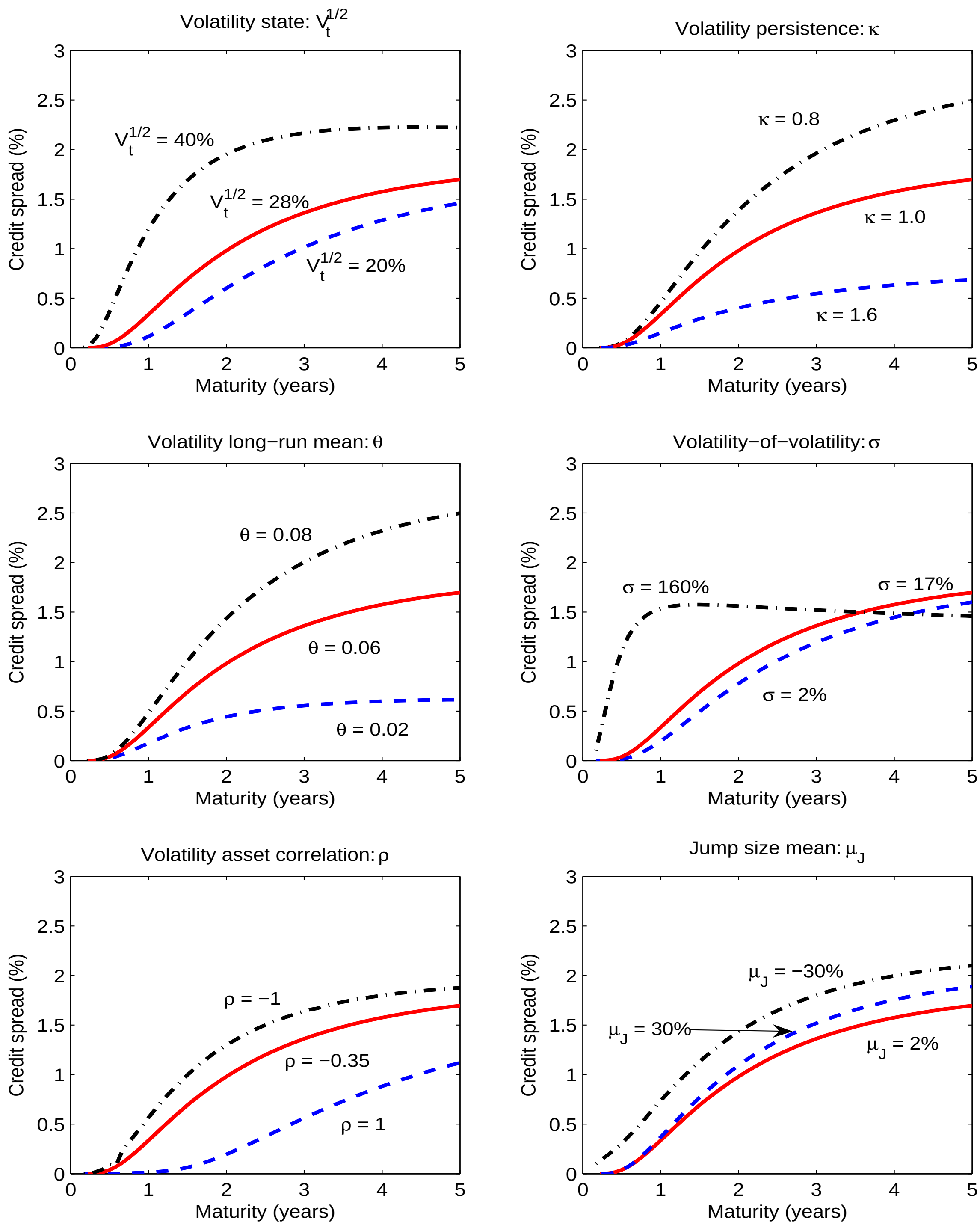


Figure 6 Linkages from asset and equity values to credit spreads

The left column plots the spread changes against the latent asset parameter changes; the right column plots the spread changes against the observed equity parameter changes.