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Combining hazard rates with the CreditGrades model: A hybrid method to value CDS contracts

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Abstract

In this paper, we propose a hybrid method that combines a hazard rate model with the CreditGrades model to value credit default swap (CDS) contracts. The CreditGrades model is considered an industry benchmark for analyzing credit derivatives. The hybrid method makes use of the default probability generated by the CreditGrades model to determine the hazard rate specific to the bond issuing firm. In this way, the hybrid method is empirically shown to produce better CDS forecast.

Keywords: Hazard rate model; CreditGrades model; credit default swap; structural model.

1. Introduction

This research proposes to combine a hazard rate model, as proposed by Lee *et al.* (2004), with the CreditGrades Model, as proposed by Finger (2002) and Stamicar and Finger (2006), to value credit default swap (CDS) contracts.

CDS contracts are credit derivatives that offer default protection to bond investors. The value of a CDS contract is usually divided into two parts, one is the

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fixed leg which is the CDS spread, paid by the CDS buyer to the seller; the other is the contingent leg which represents the contingent claim owned by the CDS buyer toward the seller. The theoretical CDS spread is determined by setting the present value of the fixed leg equal to the present value of the contingent leg. The present value of the contingent leg is in fact the present value of the default loss payments from the seller if the bond issuer defaults. It is a function of the probability of default occurring and the recovery rate.

For default modeling, two main types of models have been proposed: the structural model and the reduced form model. Both types have different definitions of the probability of default. Under the standard structural model (see the path-finding works of Merton (1974, 1976), Black and Cox (1976), and Leland (1994)), default of a firm is defined using balance-sheet notion of insolvency, with the firm's asset value assumed to follow a stochastic differential equation. Equity is considered as a call option on the underlying firm value with the strike equal to the face value of debt, and the maturity of debt equal to its repayment date. In this case, since equity is a call option, the probability of default can be inferred from the option value.

A reduced form model is also called an intensity-based model or a hazard rate model (see, for example, Lando (1998); Hull and White (2000)). The basic idea of this approach is that the dynamics of an assumed hazard rate, or the arrival intensity of default, can capture the evolution of a firm's default risk. The firm-specific hazard rate is usually modeled to follow a stochastic process and if deemed appropriate, correlated with macroeconomic variables. A risky security can then be priced as if it were a risk-free security, provided that the default intensity has taken the risk premium into account.

In theory, the probability of default generated from both types of default modeling can be used to value CDS contracts. However, the implementations may incur some concerns with insufficient information used, or inaccuracies and biases observed.

In this paper, we propose a hybrid method to value single-name CDS contracts. Essentially, we will use the framework of the hazard rate model proposed by Lee *et al.* (2004), combined with a structural model, the CreditGrades model of Finger (2002) and its extension by Stamicar and Finger (2006).

Finger (2002) derives the original CreditGrades model based mainly on Black and Cox (1976). The model is categorized as one of the structural models in that defaults occur when the random asset value crosses a random debt barrier. Under CreditGrades, only the option maturity needs to be specified since equity is defined as the difference between the asset and the recovery value. Over the years, the model has evolved as an industry benchmark for analyzing credit derivatives, including CDS contracts.

Stamicar and Finger (2006) derive analytical option formulas under the CreditGrades model framework that include both firm leverage and asset volatility. Thus, the extension provides useful links between equity and credit markets.

Like other structural models, the probability of default depends on the asset volatility. Since the asset volatility is not observable, the equity volatility is first estimated by using equity or derivative market data. Then using a theoretical relationship between the equity volatility and the asset volatility, the latter can be computed.

Therefore, for forecasting CDS spreads, the term structure of survival probabilities is required. The CreditGrade approach and the hazard rate approach use different methods to obtain survival probabilities. In the CreditGrade approach, survival probabilities are obtained using equity volatilities, which are calibrated with option-implied volatilities from stock options, or with backward-induced volatilities from historical CDS spreads. In the hazard rate approach, survival probabilities are obtained using hazard rates, which are calibrated with corporate bond spreads, or with historical CDS spreads.

However, in the CreditGrade approach, one-day estimate of survival probability is sufficient for one CDS spread forecast. While in the hazard rate approach, since the likelihood function of survival probabilities for a time period is used, it takes into account more valuable information. This reasoning is similar to the survival analysis discussed in Madorno *et al.* (2013).

In the hazard rate approach, although the concern with insufficient information is alleviated, deriving hazard rates directly from CDS spreads will be fraught with inaccuracies and biases, especially for high hazard rates, since the CDS spread model is considered not consistent with the survival analysis Berd *et al.* (2004).

Our hybrid method, while based on hazard rate models, uses fitted survival probabilities obtained from historical CDS spreads indirectly to estimate firm-hazard rates. In this way, we may avoid the less information problem in the CreditGrade model and the bias problem in the hazard rate model. Thus, the accuracy of CDS spread forecast can be improved.

The paper is arranged as follows. In Sec. 2, we briefly describe the various models. Given the model descriptions, Sec. 3 shows steps to implement the empirical studies of comparing CDS spread forecasts by the models. Section 4 presents data used and describes the testing results. Finally, Sec. 5 concludes the paper.

2. The Models

2.1. The original CreditGrades model description

The well-claimed merit of the CreditGrades model is the relation of relevant model parameters to market observables. Using the structural model framework, it models the uncertainty in the default barrier. This is a departure from the standard structural model in which an event of default occurs when the asset value of a firm crosses a predetermined default barrier or threshold. Following the model description of Finger (2002), assume the default threshold L, with an uncertainty parameter λ, the leverage ratio $d = S_0 e^{\lambda^2}/(LD)$, where S_0 is the equity value at time 0, D as the debt-per-share, a closed form formula for the survival probability up to time t is:

$$P(t) = \Phi\left(-\frac{A_t}{2} + \frac{\log(d)}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{\log(d)}{A_t}\right), \tag{1}$$

where $\Phi(\cdot) =$ the cumulative normal distribution function, $A_t^2 = \sigma_s^2 t + \lambda^2$, and $\sigma_s =$ the equity volatility.

The survival probability is one of the key inputs in the pricing process of CDS contracts.

2.2. The pricing of credit default swap contracts

Based on the survival probability of Eq. (1), the CDS spread can be obtained by equating the discounted expected loss payouts for the CDS to the discounted expected premium payments. The discounted expected loss payouts for the CDS are given by

$$(1 - R)\left[1 - P(0) + \int_0^t e^{-rs} f(s) ds\right], \tag{2}$$

where R is the asset specific recovery rate, r is the default-free discount rate and $f(s)$ is the probability density function for the default time, defined as $f(t) = -dP(t)/dt$. The discounted expected premium payments are given by

$$\mathrm{C} \int_0^{\mathrm{T}} e^{-rs} P(s) ds, \tag{3}$$

where c is the credit spread of the CDS.

The price of the CDS is then given by the difference of Eqs. (2) and (3). Therefore, for a constant risk-free interest rate r and the survival probability function, the par credit spread c for a CDS with maturity t is the spread that makes the CDS price equal to zero:

$$\mathrm{C} = (1 - R) \frac{1 - P(0) + \int_0^t e^{-rs} f(s) ds}{c \int_0^t e^{-rs} P(s) ds}. \tag{4}$$

Standard implementations of structural models, such as the above, require estimation of asset volatilities from historical equity volatilities. Stamicar and

Finger (2006) proposed an extension to the CreditGrades structural model to include implied volatilities, thus called the market-based model. The implied volatilities are useful as credit warning signals since we expect them to spike during a credit crisis. The relationship between equity volatility and asset volatility is

$$\sigma_s = \sigma\left[1 + \frac{Be^{rt}}{S}\right]. \tag{5}$$

The extension is a useful complement to the original model because it establishes a simple framework linking the credit and equity markets so as to lead to more timely credit signals and better CDS pricing.

2.3. The hazard rate model

The hazard rate model proposed by Lee *et al.* (2004), defines hazard rate λ_i for firm i, in a credit risk model based on a conditional-independence framework as:

$$\lambda_i = \lambda_{ii} + \lambda_C, \tag{6}$$

where λ_{ii} is subject to firm-specific risk, and λ_C is subject to a common risk. They use benchmark interest rates as common factor such as the rates of treasury bond, AAA corporate bond, or BBB corporate bond, as provided by Moody's Investors Service.

To distinguish the survival probability from that of the CreditGrades model, we designate the survival probability as:

$$Q_H(t) = \exp(-\lambda_i t). \tag{7}$$

Then the CDS spread will be calculated as (Stamicar and Finger, 2006):

$$c = \frac{(1-R)\left(\int_0^t e^{-rs} q(s)ds + 1 - Q_H(0)\right)}{\int_0^t e^{-rs} Q_H(s)ds}, \tag{8}$$

where the probability density function for the default time $q(t) = -dQ_H(t)/dt$. By fitting daily CDS spread and using Eq. (8), we can estimate the firm-specific λ_i.

Next, we illustrate how to apply the Cox proportional hazard rate model to compute the survival probability, the firm specific hazard rate λ_i in this case.

First, we express the firm-specific hazard rate λ_i at time t in log-linear form: $\lambda_{it} = \lambda_0 \exp[\lambda_{ii,t} + \beta r_{Bt}] = \lambda_0 \exp[\theta^T X_t]$, where λ_0 is the baseline hazard function, β the parameter to be estimated, and r_{Bt} the benchmark interest rate. Denote $\theta^T = [\,1\ \ \beta\,]$, $X_t^T = [\,\lambda_{ii,t}\ \ r_{Bt}\,]$. Thus, $\ln(\lambda_{it}/\lambda_0) = \theta^T X_t$. By partial differentiation, we get $\partial\lambda_{it}/\partial\theta = \lambda_{it} X_t$. The estimation of the unknown coefficients θ will be conducted by a maximum likelihood procedure.

Since the log-likelihood equation of the hazard rate model can be written as $\ln L = \sum_{s=1}^{t}(\ln\lambda_0 + \theta^T X_s)$, hence $\partial \ln L/\partial\theta = \sum_{s=1}^{t}(\lambda_{is}X_s)$. Thus, θ, or β, can be estimated. Because

$$\hat{\lambda}_C = \beta r_B, \tag{9}$$

so that

$$\hat{\lambda}_{ii} = \lambda_i - \hat{\lambda}_C. \tag{10}$$

3. Data Used and Model Implementations

Daily mid-market quotes on 5-year CDS spreads collected from the Bloomberg system, from the period January 2010 through June 2014. We choose ten firms chosen from diversified industrial sectors, and divide them into two groups of bond ratings: bonds rated BBB and above (the investment grade), and bonds rated BB and below (the speculative grade). In total, 1,1227 daily CDS quotes are used in the analysis.

In addition, the CreditGrades model requires some inputs to generate a CDS spread:

(i) Equity price S, Debt per share D, and Interest rate r are from Bloomberg system.
(ii) For simplicity, we assume default threshold $L = 1$, and threshold uncertainty parameter $\lambda = 0$. Time to expiration $T = 5$ for a 5-year CDS contract.
(iii) Bond-specific recovery rates R were taken from the Moody's Investors Services.
(iv) Equity volatility σ_S: The equity volatility σ_S can be either a historical volatility or an option-implied volatility. Our paper uses CDS backward-inducted volatility.

Data used for the hazard rate model are daily CDS quotes, 5-year Government and corporate bonds, Bond recovery rate R, and Time to expiration T.

Cao *et al.* (2011) use the CreditGrades model to analyze CDS spreads and demonstrate that the performance of the model can be significantly improved by calibrating it with option-implied volatility rather than with historical volatility. In comparison, we use CDS backward-inducted volatilities. Tables 1 and 2 present summary statistics of the data used.

For estimating the equity volatility, stochastic volatility (SV) models and GARCH models are two main classes. In SV models, part of the changes in volatility is due to random shocks. The volatility is driven by one of several extra

Table 1. Summary statistics, January 2010–June 2014, investment-grade corporations.

	Mean	Q1	Median	Q3	Standard deviation
CDS spread (bp)	103.25	84.37	102.73	119.87	23.98
Historical volatility	23.41%	20.56%	21.72%	25.83%	4.20%
Implied volatility	37.21%	35.29%	37.18%	38.69%	2.21%
Leverage ratio (%)	52.46	50.69	52.40	54.88	3.10
Total asset ($ billions)	143.71	128.72	135.49	154.77	23.63

Note: The above table presents summary statistics of the time series means for investment-grade sample corporations. CDS spread is the daily five-year credit default swap spread. Historical volatility is for 252 trading days. Implied volatility is the volatility inferred from CDS spreads using the CreditGrade model. Total asset is the sum of total liabilities and market capitalization, which is the product of the stock price and shares outstanding. Leverage ratio is total liabilities divided by total assets.

Table 2. Summary statistics, January 2010–June 2014, speculative-grade corporations.

	Mean	Q1	Median	Q3	Standard deviation
CDS spread (bp)	305.70	253.00	300.12	350.54	71.63
Historical volatility	34.68%	30.75%	34.79%	38.59%	6.05%
Implied volatility	51.80%	47.61%	52.27%	55.75%	5.01%
Leverage ratio (%)	59.58	57.87	59.39	62.18	3.38
Total asset ($ billions)	22.65	16.95	24.51	25.86	4.63

Note: The above table presents summary statistics of the time series means for speculative-grade sample corporations. See Notes to Table 1.

Brownian motions. As a result, perfect replication and price uniqueness are lost (Guyon, 2014).

The GARCH model assumes that the randomness of the variance process varies with the variance. At any time, only the current estimate of the volatility and the most recent observation on the stock price need to be remembered. Moreover, when a new observation on the stock price is obtained, a new daily percentage change is calculated and used to update the estimate of the equity volatility. Because a decay rate governs the impact of a new daily stock price change on the estimated equity volatility, the information of new stock prices will not be reflected in the CDS spread promptly.

Fleming and Kirby (2003) investigate the empirical performance of GARCH and SV models from both statistical and economic perspectives. They conduct pair-wise VaR comparisons to find whether differences in performance between the GARCH and SV forecasts are large enough to be economically meaningful. The results support the use of GARCH models for parameter estimation and volatility forecasting.

In the framework of Lee *et al.* (2004), the hazard rate is divided into a common factor and a firm-specific factor. The common factor is represented by a benchmark interest rate, thus taking into account the current bond market information. It is for the firm-specific factor estimation that we intend to bring in the CreditGrades model, to benefit from the current information provided by the CDS market.

In our hybrid model, equity volatility is estimated from CDS spread, instead of equity option. Hence, a GARCH model is appropriate as it does not need to consider fitness to the volatility market smile in equity option markets.

We first use historical CDS spreads to estimate equity volatilities. Then we calculate the term structure of survival probabilities. With the term structure of survival probabilities, we can calculate the implied firm-specific factor. After the common and firm-specific factors in the hazard rate are estimated, we obtain the value of CDS contracts.

In comparison, other basic hazard rate models use historical CDS spreads to compute the implied firm-specific hazard rate directly, without estimating equity volatilities.

3.1. The CreditGrades model (Model CG)

The implementation of the CreditGrades model (Model CG) is as follows:

- CG Step 1: Based on Equation (1), with an initial value of asset volatility σ, the survival probability function $P(t=1) \sim \mathrm{P}(t=5)$ can be derived. Using Eq. 4, an initial CDS spread can be calculated.
- CG Step 2: Adjusting the asset volatility σ, we make the CDS spread equal to the daily historical CDS spread so that we can obtain CDS backward-inducted asset volatility.
- CG Step 3: Using Eq. (5), we calculate the corresponding backward-inducted equity volatility. By regression the backward-inducted equity volatility on the historical equity volatility, we can forecast the backward-inducted equity volatility with daily stock prices. We then can forecast the CDS spread.

3.2. The hazard rate model (Model HZ)

The implementation of the hazard rate model (Model HZ) is as follows:

- HZ Step 1: Given the historical CDS price, we can calculate the implied hazard rate and the corresponding survival probability $Q(t=1) \sim Q(t=5)$.
- HZ Step 2: We decompose the implied hazard rate into two components: the common factor and the individual factor. The common factor is the corporate bond spread with AAA credit rating for an investment grade firm, or the spread

with BBB credit rating for a high risk grade firm. With the daily implied hazard rate, we can estimate the common factor and the individual factor using Eqs. (9) and (10), respectively. The forecasted hazard rate can then be calculated using Eq. (6).

- HZ Step 3: With the forecasted hazard rate, the expected term structure of survival probabilities $\mathrm{Q}_{\mathrm{H}}(t = 1) \sim Q_{\mathrm{H}}(t = 5)$ can then be obtained. The forecasted CDS spread can further be calculated using Eq. (8).

3.3. The hybrid model (Model HB)

In a hazard rate model, a suitable estimation of the hazard rate will lead to accurate CDS spreads. However, estimation of the hazard rate depends on the corporate default events data. The rare frequency of default events reduces the sensitivity of hazard rate to the CDS market. To address this problem, our hybrid model estimates hazard rates from the term structure of survival probabilities, which consider daily stock prices. Thus, the response of hazard rate to the CDS market can be more prompt.

Our hybrid method takes three steps to calculate CDS spread. The procedure to implement the hybrid model (Model HB) is as follows:

- HB Step 1: Using the hazard rate model, survival probability is given by Eq. (7). Then we estimate the implied hazard rate by the following minimization: $\mathrm{Min}\sum_{t=1}^{T}[Q_H(t) - P(t)]^2$, where $P(t)$ is the term structure of survival probabilities obtained from Step 1 of the CreditGrades model.
- HB Step 2: With the daily implied hazard rate, we can estimate the common factor and the individual factor using Eqs. (9) and (10) respectively.
- HB Step 3: Given the forecasted hazard rate estimated from the Poisson model, we can forecast the term structure of survival probability, and then calculate the corresponding CDS spread using Eq. (8).

Tables 3 and 4 show the estimated parameters required in the model CG, model HZ, and model HB.

Figures 1 and 2 show the estimated CDS spreads using three models.

4. Testing Results

To test the performance of the hybrid model, we compare CDS spreads using three models: the extended CreditGrades model, the hazard rate model, and the hybrid model.

The model performance can be measured by pricing errors which are model forecasted CDS spreads deviation from the observed CDS spreads. Three pricing

Table 3. Estimated implied volatility for CreditGrade models and hybrid models.

	Model CG		Model HB	
	Mean	Standard error	Mean	Standard error
Investment-grade corporations				
Historical volatility	23.41%	4.20%	23.41%	4.20%
Inducted volatility	31.76%	0.84%	37.21%	2.21%
Speculative-grade corporations				
Historical volatility	34.68%	6.05%	34.68%	6.05%
Inducted volatility	43.19%	1.21%	51.80%	5.01%

Note: "Historical volatility" denotes the equity volatility calculated directly from daily equity price. "Inducted volatility" denotes the equity volatility inducted backward from daily CDS spread.

Table 4. Estimated intensity for hazard rate models and hybrid models.

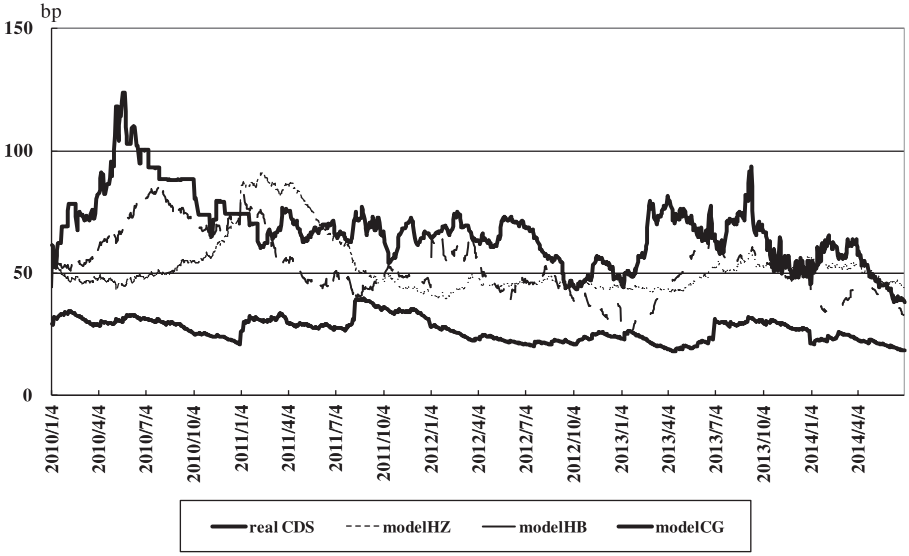
	Model HZ		Model HB	
	Mean	Standard error	Mean	Standard error
Investment-grade corporations				
Common factor	0.33%	0.14%	0.79%	0.25%
Firm-specific factor	1.36%	0.24%	0.84%	0.44%
Estimated intensity	1.69%	0.27%	1.63%	0.50%
Speculative-grade corporations				
Common factor	0.77%	0.32%	1.90%	0.59%
Firm-specific factor	4.15%	0.79%	2.90%	1.14%
Estimated intensity	4.92%	0.85%	4.80%	1.28%

Note: "Common factor" denotes the common risk factor of the estimated hazard rate. "Firm-specific factor" denotes the firm-specific risk factor of the estimated hazard rate. "Estimated intensity" is the estimated hazard rate, the sum of "Common factor" and "Firm-specific factor".

errors are often reported: the average pricing error, the average absolute pricing error, and the root-mean-square pricing error (RMSE), as defined in the following.

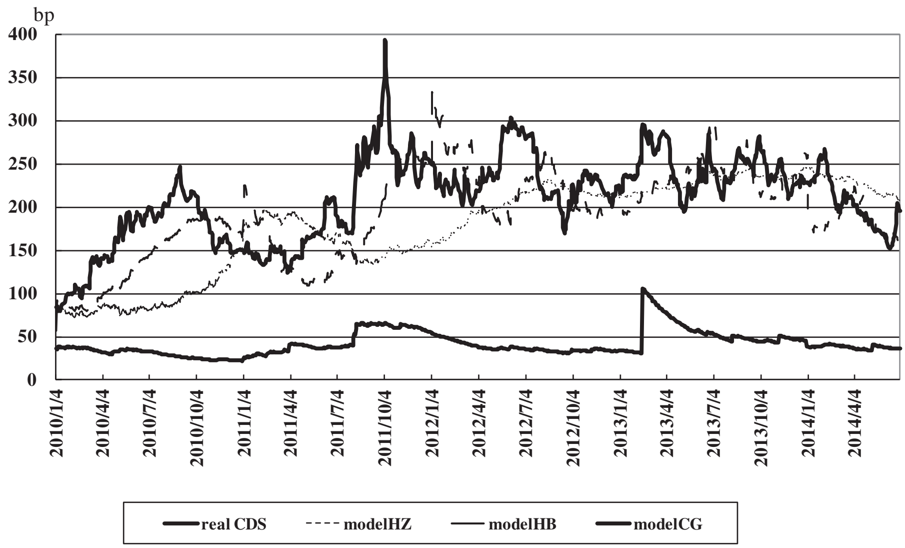
For the pricing errors parts, $\hat{c}_t$ is denoted as the estimated CDS spread at time t, and c_t is denoted as the real CDS spread at time t. Then the average pricing error $= \sum_{t=1}^{T}(\hat{c}_t - c_t)/T$, the average absolute pricing error $= \sum_{t=1}^{T} \mid \hat{c}_t - c_t \mid /T$, and the RMSE $= \sqrt{\sum_{t=1}^{T} (\hat{c}_t - c_t)^2}/T$.

For the percentage pricing errors parts, denote percentage of CDS pricing error at time $t\hat{c}_t^p$ as $\hat{c}_t^p = (\hat{c}_t - c_t)/c_t$, then the average pricing error $= \sum_{t=1}^{T} \hat{c}_t^p/T$, the average absolute pricing error $= \sum_{t=1}^{T} \mid \hat{c}_t^p \mid /T$, and the RMSE $= \sum_{t=1}^{T} \sqrt{(\hat{c}_t^p)^2}/T$.



Note: Figure 1 presents estimated CDS over time using the hazard rate model, the hybrid model, and the extended CreditGrades model, denoted by "modelHZ", "modelHB", and "modelCG", respectively. "realCDS" denotes historical CDS spreads.

Fig. 1. Estimated CDS of Verizon corporation, an investment-grade corporation.



Note: See Notes to Fig. 1.

Fig. 2. Estimated CDS of Century Link corporation, a speculative-grade corporation.

Table 5. Comparison of models for investment-grade corporations.

	Model CG		Model HZ		Model HB	
	Mean	Standard error	Mean	Standard error	Mean	Standard error
Pricing errors (bps)						
Average pricing error	−42.20	24.00	−10.16	31.99	−14.25	21.41
Average absolute pricing error	43.65	22.12	26.92	22.88	21.62	16.90
RMSE	49.43	45.44	35.42	43.10	27.53	33.72
Percentage pricing errors						
Average pricing error	−45.67%	13.75%	−11.51%	26.61%	−20.19%	16.37%
Average absolute pricing error	47.30%	11.44%	24.90%	18.69%	23.89%	13.42%
RMSE	49.27%	30.59%	31.21%	35.00%	27.51%	26.85%

Note:
1. The above table presents pricing errors on the basis of both forecasted CDS spread levels and percentage deviations from observed CDS levels.
2. In the pricing errors part, the error is calculated by the difference of the forecasted CDS spread and the observed one. In the percentage pricing errors part, the error is calculated by the difference of the forecasted CDS spread and the observed one, divided by the observed one.
3. Column "Mean" denotes means of pricing errors and percentage errors. Column "Standard Error" denotes standard deviation of pricing errors and percentage errors.
4. Row "RMSE" denotes root-mean-square pricing errors.

Table 5 compares performance of three models for investment-grade corporations by presenting averages of pricing errors. In regard to pricing errors, we found that hybrid models yielded the mean of average absolute pricing errors 21.62%, smaller than the mean value of 26.92% in hazard rate models, and also smaller than the mean value of 43.65% in CreditGrades models. It also shows that hybrid models yielded the mean of RMSEs 27.53%, smaller than the mean of RMSEs 35.42% in hazard rate models, and also smaller than the mean of RMSEs 49.43% in CreditGrades models. When using standard deviation of absolute pricing errors as performance measure, hybrid models yielded the standard error 16.9%, smaller than the standard error 22.88% in hazard rate models, and also smaller than the standard error 22.12% in CreditGrades models.

In regard to percentage pricing errors, we found that the hybrid model yielded the mean of average absolute pricing errors 23.89%, smaller than the mean value of 24.9% in the hazard rate model, and also smaller than the mean value of 47.3% in CreditGrades models. It also shows that hybrid models yielded the mean of RMSEs 27.51%, smaller than the mean of RMSEs 31.21% in hazard rate models, and also smaller than the mean of RMSEs 49.27% in CreditGrades models. The

Table 6. Comparison of models for speculative-grade corporations.

	Model CG		Model HZ		Model HB	
	Mean	Standard error	Mean	Standard error	Mean	Standard error
Pricing errors (bps)						
Average pricing error	−102.58	81.53	−8.05	88.02	−15.97	57.90
Average absolute pricing error	133.07	70.54	71.42	57.29	44.65	40.83
RMSE	152.88	145.51	91.63	112.56	60.58	84.37
Percentage pricing errors						
Average pricing error	−32.14%	17.09%	0.11%	28.48%	−5.33%	17.93%
Average absolute pricing error	47.24%	12.62%	24.47%	17.86%	15.23%	11.23%
RMSE	49.89%	31.24%	30.37%	33.80%	18.93%	21.95%

Note: See Notes to Table 5.

figures in Table 5 show that performance of the hybrid model is better than that of the hazard rate model and the CreditGrades model.

Table 6 compares performance of three models for speculative-grade corporations by presenting averages of pricing errors. In regard to pricing errors, we found that hybrid models yielded the mean of average absolute pricing errors 44.65%, smaller than the mean value of 71.42% in hazard rate models, and also smaller than the mean value of 133.07% in CreditGrades models. It also shows that hybrid models yielded the mean of RMSEs 60.58%, smaller than the mean of RMSEs 91.63% in hazard rate models, and also smaller than the mean of RMSEs 152.88% in CreditGrades models. When using standard deviation of absolute pricing errors as performance measure, hybrid models yielded the standard error 40.83%, smaller than the standard error 57.29% in hazard rate models, and also smaller than the standard error 70.54% in CreditGrades models.

In regard to percentage pricing errors, we found that hybrid models yielded the mean of average absolute pricing errors 15.27%, smaller than the mean value of 24.47% in hazard rate models, and also smaller than the mean value of 47.24% in CreditGrades models. It also shows that hybrid models yielded the mean of RMSEs 18.93%, smaller than the mean of RMSEs 30.37% in hazard rate models, and also smaller than the mean of RMSEs 49.89% in CreditGrades models.

5. Concluding Remarks

This paper a hybrid method that combines the original CreditGrades model of Finger as well as the extended version of Stamicar and Finger (2006) with a hazard rate model for calculating CDS spreads. With up-to-date data to implement the models, we make various comparisons to show the merit of the proposed hybrid method.

We empirically show that for forecasting CDS spreads, the hybrid method has the potential to yield better performances than the CreditGrades model, an industry benchmark for analyzing credit derivatives. We conjecture that the estimated firm-specific hazard rates that bring about the current bond market information, plays an important role in valuing CDS contracts.

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