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Corporate Credit Risk Prediction Under Stochastic Volatility and Jumps

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Abstract

This paper exams the impact of allowing for stochastic volatility and jumps (SVJ) in structural model on corporate credit risk prediction. The results from a simulation study verify the better performance of the SVJ model compared with the commonly used Merton model, and three sources are provided to explain the superiority. The empirical analysis on two real samples further ascertains the importance of recognizing the stochastic volatility and jumps by showing that the SVJ model decreases bias in spread prediction from the Merton model, and better explains the time variation in actual CDS spreads. The improvements are found particularly apparent in small firms or when the market is turbulent such as the recent financial crisis.

Keywords: Credit Risk, CDS Spread, Merton Model, Stochastic Volatility, Jumps.

JEL classification: C22, G13

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1 Introduction

The recent financial crisis has spurred renewed interest in developing sophisticated methods to model the corporate credit risk. Structural and reduced form approaches represent the two primary classes of such models, and play increasingly important roles in corporate risk management and performance evaluation processes. While the reduced form approach models credit defaults as exogenous events driven by a stochastic process, the structural approach provides an explicit relationship between default risk and corporate capital structure. In this sense, structural models are more referring to economic fundamentals and provide an endogenous explanation for corporate default.

The first model by Merton (1974) laid the foundation to the structural approach and this has served as the cornerstone for all other structural models. Despite the great success of the Merton model, the assumption in the model that asset return follows a pure diffusion has long been criticized. There are many studies showing that the pure diffusion assumption is overly restrictive and causes the Merton model to estimate the credit risk measures with a large bias. In theory, the log-normal pure diffusion model fails to reflect many empirical phenomena, such as the asymmetric leptokurtic distribution of the asset return, volatility smile and the large random fluctuations in asset returns. Since all of these features play key roles in structural credit risk modeling, one will produce misleading risk estimates because of ignoring them. For example, Jones et al. (1984) analyzed 177 bonds issued by 15 firms and found that the Merton model overestimated bond prices by 4.5% on average. Eom et al. (1994) empirically tested the performance of the Merton model in predicting corporate bond spreads, and suggests that the predicted spreads from the Merton model are too much lower than the true counterparts. Tarashev (2005) claimed that the default probability generated by the Merton model is significantly less than the empirical default rate, and Huang and Hao (2008) documented the inability of the existing structural models to capture the dynamic behavior of credit default swap (CDS) spreads and equity volatility. These empirical findings pointed potential roles of time-varying asset volatility and jumps in credit risk modeling.

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The objective of this paper is to generalize the structural model to allow for stochastic volatility and jumps (SVJ) in the underlying asset returns, as well as study the property of the SVJ structural model in corporate credit risk prediction. Basically, the SVJ model is not novel as it has been widely used in option pricing literature. However, its application in credit risk modeling is relatively new. The only related work was Fulop and Li (2013) which showed an application of the structural model with stochastic volatility (SV) in evaluating the credit risk of Lehman Brothers. However, their

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work mainly focused on the estimation of the SV structural model. This paper goes further to also consider jumps and examining the impact of allowing for both stochastic volatility and jumps in a structural model on corporate credit risk prediction. To our best knowledge, this is the first time an explicit study has been done on the benefit of recognizing stochastic volatility and jumps in asset returns for credit risk prediction. The research is useful for current practice where structural credit risk models with constant asset volatility still predominate. Specifically, we employ Bates (1996) model as an example of a SVJ model to describe the evolution of the asset returns. Jumps in Bates (1996) only appear in the return equation and are treated as a poisson process with constant intensity. The empirical observations in recent financial market turmoils have suggested that jumps are extreme events which tend to be clustered, and jumps in asset returns tend to be associated with an abrupt movement in asset volatility. This presents the possibility to allow for jumps in both asset returns and volatilities and therefore to use self-exciting jump clustering in structural models to improve credit risk predictions. We leave these interesting possibilities for later work.

Despite its attractiveness, the estimation of the SVJ model poses substantial challenges. In essence, the SV structural model is a non-linear and non-Gaussian state-space model. But it differs from the standard state-space model in several ways. First, after allowing the asset return to have stochastic volatility and jumps, the likelihood function of the observed equity prices is no longer available in a closed form. The commonly used MLE type estimation cannot be applied. Furthermore, the additional state variables that determine the level of volatility increase the dimension of the latent states. Thirdly, the additional jump related unknowns increase the dimension of parameter uncertainty. We employ a Bayesian learning algorithm by following the marginalized resample-move (MRM) approach of Fulop and Li (2013) to solve this estimation problem. This algorithm is able to deliver exact draws from the joint posteriors of the latent states and the static parameters.

A Monte Carlo study is conducted to examine the property of the SVJ model in corporate credit spread prediction. The exercise is based on a comprehensive set of simulation designs, which embody several features of the asset return data. To illustrate the benefit of allowing for time-varying volatility, we compare the SVJ model with the Merton model under a jump diffusion process with stochastic volatility and a pure diffusion with constant volatility. To reveal the important role of jumps, we compare the SVJ model with the SV model based on a jump diffusion process with stochastic volatility and a stochastic volatility process without jumps. The simulation results suggest that when the actual return is a pure diffusion, the results from all three models are almost identical

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with the Merton model performing slightly better. However, in more realistic situations where the actual return has a stochastic volatility or has both stochastic volatility and jumps, the SVJ and SV models largely outperform the Merton model, and the SVJ model with jumps shows further improvement over the SV model. In short, the SVJ model turns out to be the best of the models, and three sources are analyzed to show its superiority. First, the volatility dynamics and jumps allowed in the SVJ model can better depict the mean level of credit spread. Second, the SVJ model better tracks the changes in credit spread because of the time-varying volatility and the more realistic functional form between asset and equity values. Lastly, the jump component in the SVJ model better captures the extreme movements in credit spread.

We further implement the SVJ model on two real samples to empirically evaluate its ability. The first samples consists of 20 Dow Jones firms which represent the large-cap companies, and the second includes 200 firms randomly selected from CRSP which represent the general population of the US corporate sector. From each sample, we indeed find significant stochastic volatility and jumps in the asset returns. The impact of ignoring asset volatility dynamics and jumps in credit risk modeling is also studied. We find that the SVJ and SV model always provide better credit spread predictions than the Merton model, and SVJ model shows further improvement over the SV model. On average, the SVJ model raises the spread prediction from the Merton model by 6.5 basis points in the 20 Dow Jones firms, and 8 basis points in the 200 CRSP firms. Meanwhile, the SVJ model provides a better explanation of the time variation in actual 5-year CDS spreads by increasing the R^2 of the Mincer-Zarnowitz regression up to 8% and 10% in the two samples studied. These prediction improvements are found to be particularly apparent in small firms or when the market is turbulent such as in the recent financial crisis.

The remainder of this paper is organized as follows. Section 2 presents in details the SVJ model specification, estimation and application in credit risk prediction. Section 3 conducts a Monte Carlo simulation to study the property of the SVJ model in credit risk prediction. Section 5 provides two empirical analysis of the SVJ structural model using 20 Dow Jones firms and 200 randomly selected CRSP firms, and Section 4 is the conclusion.

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2 The SVJ Structural Model

In this section, we give a full description of the SVJ structural model, and introduce the marginalized resample-move algorithm of Fulop and Li (2013) which is used to estimate the SVJ structural model.

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2.1 The model description

We follow up the general set-up of the Merton model, but will decouple the constant volatility assumption to allow for stochastic volatility and jumps in asset price evolution. We define the asset value of a firm as S_t and its volatility as σ_t at time t, and describe their joint dynamics using Bates (1996) model as follows:

$$logS_t = logS_{t-1} + (\mu - \frac{1}{2}\sigma_{t-1}^2 - \lambda\overline{J})dt + \sigma_{t-1}\sqrt{dt}dW_t^S + J_t dN_t, \tag{1}$$

$$\sigma_t^2 = \sigma_{t-1}^2 + \kappa(\theta - \sigma_{t-1}^2)dt + \sigma_V \sigma_{t-1}\sqrt{dt}dW_t^\sigma \tag{2}$$

where dW_t^S and dW_t^σ are Wiener processes with correlation ρ. $J_t dN_t$ denotes the jump component where $N(t)$ is a compound Poisson process with constant intensity λ and J_t denotes the magnitude of the jump which follows a normal distribution as $log(1+J_t) \sim N(log(1+\overline{J}) - \frac{1}{2}\sigma_J^2, \sigma_J^2)$. Bates (1996) model is employed as an example of a SVJ model, and the same analysis can be easily generalized to other SVJ models.

Given that an equity and a zero-coupon debt are two types of outstanding claims of a firm, and the debt matures at time T with face value F, we have the following accounting identity which holds at every time t

$$S_t = E_t + D_t, \tag{3}$$

where E_t and D_t respectively denote the market value of equity and debt at time t. The default occurs in the event that the firm's assets are less than the face value of the debt, i.e. $S_T < F$, when debt matures. Otherwise, equity holders step in to repay the debt and keep the balance. Therefore, the payout to the debt holders at the maturity time T is

$$D_T = min(S_T, F), \tag{4}$$

and on the other side, the equity holders receive

$$E_T = max(S_T - F, 0). \tag{5}$$

Therefore, the firm's equity can be regarded as if it was a call option on the total asset value V of

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the firm with the strike price of F and the maturity date T. Assuming the risk-free interest rate is r, the equity claim in (5) can be priced at time $t < T$ according to the call option pricing formula as follows:

$$E_t = E(S_t; \sigma_t^2, F, r, T-t) = S_t P_1 - F e^{-r(T-t)} P_2 \tag{6}$$

where

$$P_j = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty Re\left(\frac{e^{-i\phi ln(K)} f_j(x, \sigma_t^2, T, \phi)}{i\phi}\right) d\phi \tag{7}$$

and

$$\begin{aligned}
&f_j = exp(A_j + B_j\sigma_t^2 + i\phi S + \lambda(T-t)(1+\overline{J})^{u_j+\frac{1}{2}} \times [(1+\overline{J})^{i\phi} e^{\delta^2(u_j i\phi - \frac{1}{2}\phi^2)} - 1]),\\
&A_j = -2\frac{u_j i\phi - \frac{1}{2}\phi^2}{\rho\sigma_v i\phi - \kappa_j + \gamma_j(1+e^{\gamma_j(T-t)})/(1-e^{\gamma_j(T-t)})},\\
&B_j = (r - \lambda\overline{J})i\phi(T-t) - \frac{\kappa\theta(T-t)}{\sigma_v^2}(\rho\sigma_v i\phi - \kappa_j - \gamma_j) - \frac{2\kappa\theta}{\sigma_v^2} log[1 + \tfrac{1}{2}(\rho\sigma_v i\phi - \kappa_j - \gamma_j)\frac{1-e^{\gamma_j(T-t)}}{\gamma_j}],\\
&\gamma_j = \sqrt{(\rho\sigma_v i\phi - \kappa_j)^2 - 2\sigma_v^2(u_j i\phi - \tfrac{1}{2}\phi^2)},\\
&u_1 = \tfrac{1}{2}, u_2 = -\tfrac{1}{2}, \kappa_1 = \kappa - \rho\sigma_v, \kappa_2 = \kappa.
\end{aligned}$$

For the ease of exposition, we impose an assumption that the stochastic volatility and jump risk premium are zeros, and therefore the parameters under objective and risk neutral measures are equivalent. Similarly, the firm's debt can be priced by regarding the payoff of the debt as the difference between a default-free debt and a put option on the total asset value of the firm with the strike price of F and the maturity date T. We will discuss this further in section 2.3.

Meanwhile, it is well documented that the observed equity prices can be contaminated by microstructure noise. The impact of the trading noise is particular large for small firms or firms in a financial distress. To incorporate the trading noise into our analysis, we follow up Duan and Fulop (2009) to assume a multiplicative error structure for the trading noise, and extend the equation (6) to

$$log(E_t) = log(E(S_t; \sigma_t^2, F, r, T-t)) + \delta v_t, \tag{8}$$

where v_t is an i.i.d normal random variable, and the option pricing function $E(S_t; \sigma_t^2, F, r, T-t)$ is as shown in equation (6). It is worth noting that the market microstructure effects are usually complex and can take many different forms. Huang and Yu (2010) modeled the microstructure noise using a Student-t distribution, and furthermore the noise is likely to be correlated with the equity value. The model estimates from the MRM algorithm would not be consistent if this effect is misspecified. We have stayed with the normal distribution assumption in the current work, and leave the further

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investigation of alternative distributions for later work.

2.2 The Model Estimation

In the absence of trading noise, the SVJ structural model is essentially a nonlinear and non-Gaussian state-space model with key features of (1) being the measurement equation, and (2) being the latent state equation. However, unlike the standard state-space model, the observation S_t in the measurement equation of this model is actually not observed. We need to use the observed equity values instead to filter the whole system. Since there is a one-to-one relationship between the equity and asset values, based on the model-implied likelihood function of the asset values, we can easily write out the likelihood function for equity values to estimate the model parameters and the latent states.

When trading noises are present, the estimation of the model parameters and the latent states becomes more complicated. The previous one-to-one relationship between equity and asset values is no longer existing. The equity values are now influenced by both the underlying asset value and the trading noise. Therefore, the estimation process becomes another filtering problem with (8) as a measurement equation, and equation (1) along with equation (2) being the latent state equations.

More specifically, let $\mathcal{F}_T$ denote a time series of the observed equity values, i.e., $\mathcal{F}_T = \{E_1, ..., E_T\}$. Θ represents the parameter vector containing eight parameters, i.e., $\Theta = \{\mu, \lambda, \overline{J}, \sigma_J, \kappa, \theta, \sigma_V, \rho\}$. x denotes the latent state variables including the asset value S_t, and its stochastic volatility process σ_t^2. Our objective is to simultaneously estimate the parameter vector Θ and the latent state variable x based on the information set $\mathcal{F}_T$. The marginalized resample-move (MRM) algorithm of Fulop and Li (2013) is employed to achieve this. The basic idea of this algorithm is that one can break up the interdependence of the hidden states and the fixed parameter by marginalizing out the states using a particle filter, and then a Bayesian resample-move algorithm can be applied to the marginalized system to improve the performance of the algorithm. Throughout the two steps, this algorithm delivers exact draws from the joint posterior distribution of the parameters and the state variables.

The estimation procedure for our particular problem using the MRM algorithm is detailed as follows. Starting from a set of weighted samples $\{(\Theta, x_{t-1}^{(n)}), \omega_{t-1}^{(n)}; n = 1, ..., N\}$ that represent the target distribution $p(\Theta, x_{1:t-1}|E_{1:t-1})$ at time $t-1$, where ω_{t-1} denotes the sample weights, we can arrive at a set of samplers representing the target distribution $p(\Theta, x_{1:t}|E_{1:t})$ at time t by working through the following steps:

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- **Step 1: Augmentation step.** For each $\Theta^{(n)}$, we ran a localized particle filter (see Duan and Fulop (2009)) that takes the information of the new observation E_t to propagate $\{x_{t-1}^{(k,n)}, k = 1, ..., M\}$ to $\{x_t^{(k,n)}, k = 1, ..., M\}$ via $p(x_t|x_{t-1}^{(n)}, E_t, \Theta^{(n)})$. Notice that for each n, the hidden state x_t is represented by M particles. Therefore, we have to maintain $M \times N$ particles of the hidden states throughout the whole process.

- **Step 2: Re-weighting step.** We update the weights accounting for the new information in E_t to obtained a new set of weighted samples. The incremental weights can be computed by using the likelihood $p(E_t|x_t^{(n)}, |x_{t-1}^{(n)}, \Theta^{(n)})$, and the new weights for each particle is as follows

$$s_t^{(n)} = s_{t-1}^{(n)} \times p(E_t|x_t^{(n)}, |x_{t-1}^{(n)}, \Theta^{(n)}). \tag{9}$$

  Then, our target distribution $p(\Theta, x_{1:t}|E_{1:t})$ can be represented by a new set of weighted samples $\{x_t^{(n)}, \Theta^{(n)}; n = 1, ..., N\}$.

- **Step 3: Resample-move step.** This is not necessary for all the time points. It is only implemented to enrich the set of particles and avoid a gradual deterioration of the performance of the algorithm whenever the effective sample size $ESS_t = \frac{1}{\sum_{K=1}^{n}(\pi_t^{(k)})^2}$ falls below some fixed value B_1, where $\pi_t^{(n)} = \frac{s_t^{(n)}}{\sum_{K=1}^{n} s_t^{(k)}}$ is the normalized weight. There are two steps involved: 1) Resample the particles according to the normalized weight $\pi_t^{(n)}$ to get an equally-weighted sample $\{x_t^{(n)}, \Theta^{(n)}; n = 1, ..., N\}$; 2) Then move each particle through a Metropolis-Hastings kernel to improve its support and diversity. More details are available in Fulop and Li (2013).

Meanwhile, this algorithm provides a natural estimate of the marginal likelihood for each new observation E_t, which embeds the model fit information over time and can be used to construct a sequential Bayes factor for sequential model comparison. The Bayes factor at time t for any models M_1 and M_2 has a recursive formula as follows:

$$BF_t \equiv \frac{p(E_{1:t}|M_1)}{p(E_{1:t}|M_2)} = \frac{p(E_t|E_{1:t-1}, M_1)}{p(E_t|E_{1:t-1}, M_2)} BF_{t-1}, \tag{10}$$

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where $p(E_t|E_{1:t-1}, M_i)$ is the estimate of the marginal likelihood of the new observation E_t based on model M_i.

2.3 The Model Application in Credit Risk Measurement

Once the model estimation is completed, the most appealing application of it is to predict corporate bond credit spread. The credit spread of a risky corporate bond is defined as the premium required to compensate for the expected loss in the event of default. That is, $s_t = y_t - r$, where y_t is the yield of the risky corporate bond, and r is the risk-free interest rate. As discussed in section 2.1, the risky debt can be priced by the difference between a default-free debt and a put option on the total asset value S_t of the firm with the strike price of F and the maturity date T. Therefore, the risky bond can be priced at time $t < T$ as

$$B_t = Fe^{-r(T-t)} - P_t^{HM}, \tag{11}$$

where F is the face value of the zero coupon debt at the maturity time, and P_t^{HM} is the price of a put option on the asset value S_t with the strike price F and the maturity date T [1]

$$P_t^{HM} = Fe^{-r(T-t)}(1 - P_2) - S_t(1 - P_1). \tag{12}$$

Note that our current analysis relies on the posterior expectation of parameters and states to compute the debt price without considering parameter and state uncertainties. Korteweg and Polson (2010) documented the importance of accounting for parameter uncertainty on corporate bond credit spreads, and therefore it would be interesting to conduct the same analysis by considering this effect. We leave this for later work.

According to the relationship between face value and the price of the bond, the yield y_t of the risky corporate bond can be derived from

$$e^{-y_t(T-t)}F = B_t, \tag{13}$$

[1] We refer to section 2.1 for the explicit expressions of P_1 and P_2.

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and thereby the credit spread s_t can be computed as

$$s_t = -\frac{1}{T-t}\ln(1-\frac{P_t^{HM}}{Fe^{-r(T-t)}}). \tag{14}$$

3 Monte Carlo Analysis

In this section, we conduct a simulation study of the properties of the SVJ model while comparing its performance with the Merton model and SV model without jumps, for corporate credit spread prediction. We designed three simulation scenarios to reflect the different features of the return data, including a simple pure diffusion (in which the stochastic volatility and jump related parameters (κ, θ, σ_V, λ, $\overline{J} = 0.002$, and $\sigma_J = 0.3256$) in equation (1) and (2) are set at zeroes), a stochastic volatility process without jumps (in which the jump related parameters (λ, $\overline{J} = 0.002$, and $\sigma_J = 0.3256$) in equation (1) and (2) are set at zero) and a jump diffusion process with stochastic volatility (which is exactly as jointly expressed in equation (1) and (2)). The first two scenarios aimed to illustrate the benefit of allowing for time-varying volatility in asset returns, and the last two scenarios are used to reveal the importance of jumps.

3.1 Simulation Design

Most of the parameters in the simulation are set according to Lehman Brothers analysis of Fulop and Li (2013), with $\mu = -0.034$, $\kappa = 13.93$, $\theta = 0.004$, $\sigma_V = 0.263$, $\rho = 0$, $\delta = 0.0018$, and $F = 2.734\times 10^5$. The three additional jump related parameters are calibrated to the mean estimates of our empirical data as $\lambda = 0.0032$, $\overline{J} = 0.0029$, and $\sigma_J = 0.3274$. We set the risk free rate as 0.03[2], and choose the initial leverage ratio $\frac{F}{S}$ to be 20%, resulting in the initial asset value $S_1 = 1.37\times 10^6$, and the initial value of the asset volatility is to be θ. We repeated the simulation exercise by changing the value of θ from 0.004 to 0.04 in order to investigate how the model performance changes with the increase of the firm's financial risk, and then changed the value of λ (and $\overline{J}$) from 0.0032 (and 0.0029) to 0.010 (and 0.010) to analyze the sensitivity of the model performance to the extension of jump activities in the asset returns.

In short, we generated 1250 (5-year) daily returns and then computed the firm's asset values backward to yield a sample of 1251 asset values. The equity values are calculated using the option pricing formula displayed in equation (6), and the maturity period of the firm's debt is chosen to

[2]It is the average of 3-month constant maturity treasury yield used in Fulop and Li (2013)

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be 5 years. To mimic the real world, we regarded the asset price value as an unknown, and only utilized the information embedded in the observed equity values to estimate the models. The first 1000 observations are used to estimate the models, and the last 250 observations are left for out-of-sample prediction evaluation. To lock out Monte Carlo variability, we simulated 100 data sets for each case, and implemented 15 independent runs of the MRM algorithm on each data set to get the model parameter estimates. The number of parameter and state particles used in MRM algorithm are respectively chosen to be $N = 1000$ and $M = 500$. We computed both one-step-ahead and five-step-ahead credit spread forecasts from the SVJ model, and compared its performance with the Merton model and the SV model without jumps.

3.2 Simulation Results

We computed the bias and RMSE of credit spread predictions from the three models[3] for the last 250 samples of each data set, and reported the mean of bias and RMSE across the 100 data sets in Table 1. The first column[4] contains the results for the Merton model, the fouth column has the results for SV model, and the results of SVJ model are presented in the fifth column. These results reveal several noteworthy points. Beginning with the first DGP where asset return follows a pure diffusion process (see Panel A of Table 1), where the three models performed almost identically with the Merton model performing slightly better. It is not surprising given that a complex model with more parameters (the SV model and SVJ model) will have additional estimation uncertainty. But the cost appears very small according to the results. Secondly, when the asset returns do not follow a pure diffusion (see Panel B and C of Table 1), the SVJ model largely outperforms the Merton model with a far smaller bias and RMSE. Compared with the SV model without jumps, the SVJ model performs in a similar manner when asset returns move without jumps, but performs better when asset returns follow a jump diffusion process. In addition, the improvement from the SV model to the SVJ model is more pronounced when both the intensity and magnitude of jumps increases. Thirdly, while the three models provide better forecasts at shorter time horizons (one-step-ahead), the improvement from the Merton model to the SV and SVJ models becomes more pronounced

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[3]The model predicted spread can be calculated according to the equation (14) for the SVJ model and the SV model with the corresponding P_t^{HM}. The Merton model predicted spread can be computed as follows:

$$CDS_{Merton} = -\frac{1}{T-t} log(\frac{V_t}{F}\Phi(-d_t) + e^{-r(T-t)}\Phi(d_t - \sigma\sqrt{T-t})) - r,$$

where $d_t = \frac{ln(\frac{V_t}{F}) + (r + \frac{\sigma^2}{2})(T-t)}{\sigma\sqrt{T-t}}$.

[4]The far left-hand two columns are captions.

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in longer horizon forecasts (five-step-ahead). Lastly, as the firms' financial risk increases, all the models perform worse with a larger prediction bias and RMSE. It implies that the higher the risk is, the harder it is to be accurately quantified.

Although the results reveal the advantage of SVJ model, they give no indication about where the better performance of the SVJ model comes from. We conducted a decomposition analysis on the reported RMSE to answer this question. Intuitively, we can think of at least three channels which are driving the model performance differences. Firstly, from the mean level perspective, after allowing for the dynamics in asset volatility, the SV and SVJ models can better capture the average level of the asset volatility, and thereby better predict the average level of credit spread. Secondly, with time-varying volatility and the implied more realistic functional form between asset and equity values, the SVJ model can better track the changes in credit spread. Lastly, explicitly considering jumps in the SVJ model can better describe the large random fluctuations in credit spreads. The three effects are further examined as follows.

The mean level effect can be easily identified by looking at the mean spread forecast errors of these models. We compared the average of the predicted spreads from the three models against the average of the true spreads, that is the bias we reported in Table 1. Compared to the Merton model, the always smaller bias in the SVJ and SV models verifies that taking into account the stochastic property of the asset volatility provides more accurate measurements in the level of credit spread on average.

Next, we focused on the change effect and defined a new SV model where the volatility state variable is fixed at its stationary level (that is θ) to separately explore the role of time-varying volatility and the functional form between asset and equity values in tracking the changes of credit spreads. The bias and RMSE of predictions from this new SV model are reported in the third column of Table 1. While the reduction in bias from the Merton model to this SV model implies that an appropriate functional form between asset and equity values helps better capture the changes in credit spreads, the rest of the discrepancy between this model and the SV model reveals the benefit of allowing for time-varying volatility. In fact, the two effects can be alternatively separated by looking at a modified Merton model where the asset volatility is no longer an unknown parameter, but takes its true value at each time point. This model eliminates the asset volatility estimation uncertainty, and only focuses on the effect of functional form mapping of asset values to equity values. To save space, we have not reported the results of this model, but these results are available upon request. We observe a reduction of bias and RMSE from the Merton model to this model,

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which reveals the importance of accurately estimating asset volatility in credit risk prediction. The still better performance of the SV model compared to this model reveals the benefit of utilizing an appropriate option pricing function form in structural models. At the end, we compared the SVJ model with the SV model to identify the extreme movement effect. The reduction of bias and RMSE from SV model to SVJ model under the jump diffusion process with stochastic volatility provides the evidence that explicitly modeling jumps can better capture the large fluctuations in credit spreads.

In addition, a typical implementation of the Merton model tends to use a one-year rolling window to account for time-varying asset volatility. For better comparability, we estimate the Merton model with one-year rolling samples, and reported the bias and RMSE of the generated predictions in the second column of Table 1. In general, both bias and RMSE are reduced from the previous Merton model with multi-year fixed samples. This improvement further justifies the benefit of taking into account the variability of the asset volatility. More importantly, the rolling strategy does not help the Merton model to overcome the SV and SVJ models decisively. The still smaller bias and RMSE of the SV and SVJ models suggest that apart from specifying the dynamics of time-varying volatility, other aspects or features are leading to the better performance of the two models such as the functional form transforming asset values to equity values.

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4 Empirical Analysis

We apply the SVJ structural model on two real data sets to empirically assess its ability in credit risk predictions. The first sample includes 20 Dow Jones firms representing the large-cap companies, and the second contains 200 randomly selected firms from the CRSP database representing typical U.S. exchange listed firms. The firm is included in the second sample only if it has the required CDS spread data and balance sheet information for our sample period and it is not a firm already contained in the Dow Jones sample. We will compare the SVJ model with the Merton and SV models in terms of their 5-year CDS spread predictions for these sample firms. We choose CDS spreads to test the model performance due to three reasons. Firstly, the CDS contract is typically traded on standardized terms, and the transaction data is available publicly. Secondly, CDS spread is a relatively pure pricing of default risk of the underlying entity. Lastly, in the short run CDS spreads tend to efficiently respond to changes in credit conditions, so that it is a good credit risk indicator.

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4.1 Dow Jones 20 Firms

Our data sample consists of daily 5-year corporate debt CDS spreads[5], and all the required balance sheet information of the 20 firms. The sample covers the period from 03/01/2008 to 31/12/2013, resulting in a sample size of $T = 1490$. The data of CDS spreads are taken from Bloomberg, and the balance sheet information are obtained from the WRDS CRSP database. The equity values are computed as the product of the closing price of equity and the number of shares outstanding. The maturity of debt is set to 5 years to match with the maturity period of the CDS contracts, and the 3-month constant maturity treasury yield from the St. Louis FED website is chosen to represent the risk free rate. The face value of the debt F is treated as an unknown which is determined by the data. Company name and main statistics of their 5-year CDS spreads are summarized in Table 2, and Figure 1 displays the average daily equity return and the average 5-year CDS spreads across the 20 Dow Jones Firms over the whole sample period. The relatively higher return volatility and CDS spreads during 2008-2009 suggests the presence of a turbulent period during the recent financial crisis.

We use the first 993 samples from January 2 2008 to December 30 2011 to estimate the models, and leave the last 498 days from January 3, 2012 to December 30, 2013 for model forecast evaluation. The MRM algorithm is implemented with 1000 parameter particles (N=1000) and 500 state particles (M=500) for each parameter set. A uniform prior for F is used with a lower bound equal to current liabilities plus 0.5 long term debt (default barrier as used in Moody's KMV model) and an upper bound equal to total liabilities. The remaining parameters have the following priors: $\mu \sim N(0, 005)$, $(\theta, \kappa, \sigma_V, \lambda, \overline{J}, \sigma_J, \delta) \sim U[(0.001^2, 0, 1 \times 10^5, 0.001, -0.01, 0.01, 1 \times 10^6), (0.2^2, 20, 2, 0.01, 0.01, 0.1, 0.05)]$. Both one-step-ahead and five-step-ahead forecasts are computed for model comparison.

Table 3 reports the estimation results of the SVJ model for the 20 firms[6]. Firm names are given in the first column. Full-sample parameter posterior means together with the 5th and 95th percentiles of the posterior distribution are contained in the next columns. The mean of the log marginal likelihood is presented in the last column. Figure 2 shows the average sequential estimates of the filtered asset volatility across these firms along with the average central 90% confidence interval. These results strongly support the SVJ model from several aspects. First, the stochastic volatility related parameters (κ and σ_V) in all the firms have narrow 90% confidence intervals indicating that

[5] We choose 5-year CDS as it is the most liquid CDS contract traded in U.S market.

[6] The estimation results of the Merton model and SV model are not reported here, but they are available upon request.

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the real asset volatility indeed exhibits variability. This is further corroborated by Figure 2 in which the average value of the filtered asset volatility across the 20 firms varies substantially over time with a tight 90% confidence interval. These filtered asset volatilities can efficiently depict all fluctuations observed in the market with large magnitude and variability in the beginning of the sample, and relatively small values from the middle towards the end. Second, the jump related parameters (λ, $\overline{J}$ and σ_J) in all the firms also have tight 90% confidence intervals, but the intervals are relatively large compared to those of other parameters. These results confirm the existence of abrupt movements in asset returns, and the greater uncertainty of these extreme events occurrences. Third, the mean of the log marginal likelihood from the SVJ model is always larger than that of Merton model and SV model (the mean of the log marginal likelihood of the Merton and SV models are not reported here, but available upon request) for all the firms, implying that on average the SVJ model provides a better in-sample fit for the observed equity values on average. We also employed sequential log Bayes factor as shown in equation (10) to compare the three models recursively. We averaged the log Bayes factor between the SVJ model and the Merton model or the SV model across the 20 firms, and plot them in Figure 3. It is clear that while the three models perform similarly at the beginning, the SVJ and SV models show a huge superiority to the Merton model during the crisis period as the log Bayes factor between the SVJ model (or the SV model) and the Merton model reaches a high level at the end of year 2008 and keeps rising onwards until the end of the sample. A further advantage is noted between the SV model and SVJ model. In summary, the SVJ model is overwhelmingly preferable to Merton model and also superior to the SV model. The advantage is particularly apparent when the market is turbulent.

After obtaining the model parameter estimates, together with the risk-free interest rate we can produce the model implied credit spreads for the whole sample period. To remove the influence of the priors, we leave an initial learning period of 100 days and begin the spread calculation only after that. In contrast to the estimation period where the spreads are computed by using estimated asset volatilities, the spread predictions in the forecast evaluation period are computed using the predicted asset volatilities. By employing a 5-year CDS spread as a proxy of the real credit risk, we compare the SVJ model with the Merton and SV models in terms of bias and RMSE of their one-step-ahead and five-step-ahead credit spread predictions. The bias and RMSE of the model predicted spread have the standard definition as $E(CDS - C\hat{D}S)$, and $\sqrt{E(CDS - C\hat{D}S)^2}$, where $C\hat{D}S$ is the model predicted credit spread and CDS is the actually observed CDS spread.

We firstly look at the model implied CDS spreads in estimation period. Table 4 panel A sum-

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marizes the bias and RMSE of the model implied credit spreads for the whole estimation period, and panel B provides the results for the financial crisis period. Firm names are given in the first column. The second and third columns report the results of the Merton model, the eighth and ninth columns contain the results of the SV model, and the last two columns present the results of the SVJ model. In general, although all the three models underestimate the credit spread, there are large improvements from Merton model to SV model and SVJ model. The average RMSE across the firms are reduced around 6 basis points from Merton model to SV model, and further 2 basis points to SVJ model. The improvement is more pronounced during the crisis period, with the average RMSE decreasing respectively around 7 and 10 basis points from Merton model to SV model and SVJ model. We further examine whether the three sources documented in Section 3 are able to explain these improvements. In terms of the mean level estimation, the SV model successfully reduces the bias from the Merton model by 5 basis points, and the SVJ model reduces the bias by 6.5 basis points on average. The bias reduction appears larger during the crisis period, with 7 basis points achieved by the SV model and 9.5 basis points produced by the SVJ model. Next, we shift attention to the change effect. We computed the implied spreads from a new SV model where the state volatility is fixed at its stationary level to explore the role of time-varying volatility. The bias and RMSE of the implied credit spreads from this model are reported in the sixth and seventh columns of Table 4. While the large bias reduction from Merton model to this model shows that the mean level effect has been successfully controlled, the still larger RMSE compared to that of the standard SV model indicates that allowing for asset volatility dynamics helps better track the dynamic changes of the credit spreads. We also estimate the Merton model using one-year rolling samples, and present the results in the fourth and fifth columns of Table 4. The reduced bias and RMSE from the Merton model with a multi-year fixed sample provides the evidence that the rolling window estimation is a good way to account for the time-varying volatility. However, the still smaller bias and RMSE provided by the SV and SVJ models corroborate the fact that apart from time-varying volatility, other sources are leading to the superiority of the SV and SVJ models such as an appropriate functional form between the asset and the equity values. Lastly, we compared the SV and SVJ models to reveal the role of jumps. The always lower bias and RMSE from the SVJ model particularly during the crisis period confirms that explicitly modeling jumps can better describe the extreme movements in CDS spreads.

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Now, we turn to the model predicted CDS spreads in the forecast evaluation period. Table 5 summarizes the bias and RMSE of the spread predictions for the last 498 days of our sample

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period, with panel A for one-step-ahead forecasts and panel B for five-step-ahead forecasts. In general, the ranking of the models we observed above is still preserved here. The SV and SVJ models largely reduce the prediction bias and RMSE compared to the Merton model in all cases, and these improvements can be attributed to the time-varying volatility and the resulting option pricing formula which transforms the asset values to the equity values. The further bias and RMSE reductions are still detected from SV model to SVJ model, suggesting that explicitly modeling jumps is important to predict the CDS spread. Meanwhile, these results reveal two additional interesting findings. First, the five-step-ahead predictions from all the models have larger bias and RMSE than those of one-step-ahead counterparts, implying that obtaining an accurate forecast is more difficult in multi-step-ahead scenarios because of the accumulated forecast errors. More importantly, the prediction improvements from the Merton model to the SV and SVJ models appear greater at a longer horizon. While the average bias and RMSE across these firms respectively decreased by 4 and 5 basis points from the Merton model to the SV model, and a further reduction of 1.5 and 1.7 basis points from the SV model to the SVJ model for the daily horizon (one-step-ahead forecast), the average bias and RMSE are reduced by 5.5 and 6 basis points from the Merton model to the SV model, and decrease 1.7 and 2.5 more basis points from the SV model to the SVJ model for the weekly horizon (five-step-ahead forecast). In summary, ignoring the dynamics of asset volatility and jumps has a larger impact on longer horizon credit spread prediction.

These findings are further illustrated in Figure 4 which gives a good visual impression. The figure shows the Merton, the SV and the SVJ models predicted spreads against the actual 5-year CDS spreads of Chevron over the whole sample period. The top, middle and bottom panels of Figure 4 respectively present the implied spreads from the Merton, the SV and the SVJ models against the actual 5-year CDS spreads. While the right y-axis labels the scale of the model predicted credit spreads, the left y-axis labels the scale of the actual CDS spreads. Apparently, the predicted spreads from the SV and SVJ models track the actual 5-year CDS spreads much better than the counterparts from the Merton model with respect to both the level magnitude and the dynamic changes. The SVJ model offers further improvement over the SV model in capturing the large spikes in the actual CDS spreads. These improvements are particularly clear when market is turbulent from 01/09/2008 to 31/12/2009.

Lastly, we employ a time series regression along with the Diebold and Mariano (1995) (DM) test to reveal whether the above-documented prediction improvements are statistically significant. More specifically, we regress the 498 predicted spreads from each model on the actual CDS spreads for

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each firm as

$$CDS_{i,t} = \alpha_0 + \alpha_1 ICDS_{i,t} + \varepsilon_{i,t}, i = 1, ..., 20 \tag{15}$$

where $CDS_{i,t}$ is the actual 5-year CDS spread of firm i at time t, and $ICDS_{i,t}$ is the model predicted spread of firm i at time t.

To test for the significance of prediction bias, and separate the contribution of the mean level effect (bias) from the model's ability to explain the time-series variability (changes) of the spreads in the overall forecast accuracy, we firstly run the regression by restricting $\alpha_1 = 1$. By doing so, we can test for bias on the estimate of α_0, and measure the property of the model to explain time-variation of the actual spreads using the sum-of-squared errors of the fitted regression (as the estimated α_0 takes out the effect of bias). The summary statistics of the restricted regression estimation results for the 20 firms are presented in Table 6, and the results for each individual firm are available upon request. We report R^2 instead of the sum-of-squared errors of the fitted regression, as the two measures convey the same information, but the former is better to show how much time-variation of the actual spreads has been explained by the model predicted ones. Consistent with our expectation, the estimates of α_0 are exactly the same as the bias we reported in Table 5. Meanwhile, the estimated values of α_0 are positive, and statistically significant at the 5% significance level. More importantly, while the estimated value of α_0 decreases from the Merton model to the SV model and again to the SVJ model, the R^2 increases across these models. These findings once again suggest that although all the structural models considered here under-predict the actual credit spreads, the under-prediction is largely improved after taking into account the stochastic property of the asset volatility and jumps. Meanwhile, apart from the mean level effect, allowing for time-varying volatility and jumps can better track the time-variation of the actual spreads. We further use the DM test to examine whether these improvements are statistically significant[7]. In all cases there are significant improvements from the Merton model to the SV model and the SVJ model in terms of both bias reduction and time-variation explanation. In most cases with four exceptions in one step-ahead forecasts and three exceptions in five-step-ahead forecasts there are further improvements from the SV model to the SVJ model.

Next, we run the same regression exercises and across-model comparison without the restriction on α_1 to test the improvements on overall forecast accuracy. The summary statistics of the regression

[7]The significance of the bias reduction is tested relying on a time series of $CDS_{i,t} - ICDS_{i,t}$ from each model, and as the estimated α_0 removes the effect of bias, the significance of the improvements in time-variation explanation is tested by looking at the squared residuals from the restricted regressions.

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results are presented in Table 7. Despite the optimal forecast hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$ is rejected in all the model predicted spreads, there is a clear trend that the positive values of β_0 decreases towards zero and the values of β_1 decreases towards one from the Merton model to the SV model and again to the SVJ model. These provide supportive evidences that to some extent the biased and inefficient spread predictions from the Merton model are improved by the SV and SVJ models. This is further corroborated by the increase of R^2 across these models in all the cases. We conduct the DM test again on the squared residuals of these regressions, and the test results suggest that in all the cases there are significant improvements from the Merton model to the SV model and the SVJ model, and in most cases with three exceptions in one step-ahead forecasts and two exceptions in five-step-ahead forecasts there are further improvements from the SV model to the SVJ model.

In addition, we test whether the orthogonal information among these models has added prediction power for credit spread. We regress the Merton model predicted spreads on the SV model predicted spreads to generate a variable $ICDS(SV - MER)_{i,t}$ that contains information from the SV model orthogonal to the Merton model:

$$ICDS(SV)_{i,t} = \beta_0 + \beta_1 ICDS(MER)_{i,t} + \varepsilon_{i,t}, i = 1, ..., 20, \tag{16}$$

where $ICDS(SV - MER)_{i,t}$ equals $\beta_0 + \varepsilon_{i,t}$. Then, we include $ICDS(SV - MER)_{i,t}$ as an extra explanatory variable in the regression(15) to test whether the SV model carries on incremental information to the Merton model in credit spread prediction. If this is true, the coefficient of $ICDS(SV - MER)_t$ should be significantly positive, and R^2 of the fitted regression should increase from the corresponding ones reported in Table 7. The summary statistics of the regression results are presented in Table 8. The significantly positive α_2 and the increase of R^2 in all the cases indicates that the SV model entails extra information for credit spread prediction. We also conduct the same exercise on the SV model and the SVJ model to test the addictive power of jumps, and the summary statistics of the test results are reported in Table 9. Most of the estimated α_2 in the table are significantly positive with three exceptions. A further increase of R^2 in all the cases confirms that more predictive information is provided by the SVJ model.

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4.2 CRSP 200 Firms

In addition to the 20 Dow Jones firms, we also analyzed 200 randomly selected firms from the CRSP to see the impact of stochastic volatility and jumps on the credit spread prediction of the typical U.S. exchange listed firms. A firm is included only if it is not a firm in the Dow Jones samples, and it has required CDS spread data along with the balance sheet information from year 2008-2013. For these sample firms, we implemented the MRM algorithm to estimate the SVJ model with the first 993 observations from January 2 2008 to December 30 2011 and compared its ability with the Merton model and SV models for the 5-year CDS spread in the last 498 days from January 3, 2012 to December 30, 2013. To save the space, we have only reported the summary statistics of the model estimation results in Table 10 and the 5-year CDS spread prediction results in Table 11. The summary statistics of the regression based test results are presented in Table 12.

As expected, the results are stronger than those of 20 Dow Jones firms, implying that explicitly considering stochastic volatility and jumps are particularly important for relatively small firms. On average, the asset volatilities of these firms exhibit more volatile as suggested by the larger mean value of the estimated σ_V, and the jumps occurred more frequently with larger size as implied by the mean value of the estimated λ and $\overline{J}$. The SV and SVJ models still largely outperform the Merton model in both short and long horizon forecasts with the SVJ model always performing the best. The average prediction improvements appear slightly greater than those in Dow Jones firms, with bias reduction of 6.1 basis points and RMSE decreasing by 7 basis point from the Merton model to SV model, and further 2 and 2.5 basis points of bias and RMSE reductions from the SV model to the SVJ model. These improvements are statistically significant according to the regression based tests. Once again, the SVJ model carries incrementally more information than the Merton model and the SV model for the prediction of 5-year CDS spreads of these firms.

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5 Conclusion

This paper extends the Merton model to allow for time-varying volatility and jumps in structural credit risk modeling. The impact of considering these two components on credit risk prediction is also studied. Our simulation experiment shows that with the presence of stochastic asset volatility, the structural model performance is largely improved in terms of both daily and weekly credit spread prediction. Further improvements are detected after adding the ability to account for jumps. These improvements in CDS spread prediction can be attributed to three sources including better mean

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level estimation, better track of the dynamic changes, and better capture of extreme movements or jumps. We further implemented the SVJ structural model on 20 Dow Jones firms and 200 CRSP firms to test its ability in real data. Our empirical results suggest ignoring asset volatility variability and jumps would lead to a significant underprediction of the corporate credit risk, and the underprediction is more severe when considering small firms. Although our methodological development is presented specifically for the Bates (1996) model, all the analysis here can be very easily adapted to other SVJ models. In conclusion, a SVJ structural credit risk model has been developed to measure the corporate credit risk exposure, and the importance of allowing for asset volatility dynamics and jumps in credit risk modeling is also documented.

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Table 1: Simulation study for the model comparison

		Merton Model	Merton Model*	SV model*	SV model	SVJ model
		Panel A: Constant Volatility without Jumps				
One step ahead	Bias	-0.0005	-0.0004	-0.0004	-0.0006	-0.0006
	RMSE	0.0009	0.0008	0.0008	0.0011	0.0011
Five step ahead	Bias	-0.0012	-0.0011	-0.0011	-0.0012	-0.0012
	RMSE	0.0015	0.0015	0.0015	0.0016	0.0016
		Panel B: Stochastic Volatility Process without Jumps				
		$\sigma_v = 0.004$				
One step ahead	Bias	-0.0052	-0.0050	-0.0051	-0.0047	-0.0047
	RMSE	0.0061	0.0059	0.0060	0.0056	0.0057
Five step ahead	Bias	-0.0057	-0.0054	-0.0053	-0.0049	-0.0050
	RMSE	0.0063	0.0061	0.0061	0.0058	0.0059
		$\sigma_v = 0.04$				
One step ahead	Bias	-0.0074	-0.0072	-0.0072	-0.0069	-0.0070
	RMSE	0.0083	0.0079	0.0080	0.0076	0.0078
Five step ahead	Bias	-0.0079	-0.0075	-0.0074	-0.0071	-0.0072
	RMSE	0.0087	0.0083	0.0082	0.0079	0.0080
		Panel C: Jump Diffusion Process with Stochastic Volatility				
		$\sigma_v = 0.004,\ \lambda = 0.0032,\ \overline{J} = 0.0029$				
One step ahead	Bias	-0.0068	-0.0065	-0.0066	-0.0062	-0.0060
	RMSE	0.0063	0.0059	0.0060	0.0056	0.0054
Five step ahead	Bias	-0.0073	-0.0068	-0.0070	-0.0067	-0.0066
	RMSE	0.0067	0.0064	0.0065	0.0062	0.0060
		$\sigma_v = 0.004,\ \lambda = 0.010,\ \overline{J} = 0.010$				
One step ahead	Bias	-0.0084	-0.0080	-0.0081	-0.0078	-0.0073
	RMSE	0.0089	0.0086	0.0087	0.0081	0.0078
Five step ahead	Bias	-0.0090	-0.0087	-0.0086	-0.0082	-0.0079
	RMSE	0.0090	0.0087	0.0088	0.0085	0.0081

Note: We simulate 100 data sets with sample size $T = 1250$ under three GDPs, including a pure diffusion, a stochastic volatility process without jumps and a jump diffusion process. We implement 15 independent runs of MRM algorithm on the first 1000 observations of each data set to obtain the model parameter estimates, and then produce the credit spread prediction for the last 250 days. This table reports the mean of bias and RMSE of credit spread predictions for the last 250 days from different models across the 100 data sets. Merton model* denotes the Merton model with rollowing samples, and SV model* denotes the artificial SV model with the volatility state variable being fixed at its stationary level.

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Table 2: Summary Statistics of 5-year CDS Spreads for 20 Dow Jones Companies

Company Name	Jan 2008-Dec 2013			
	5 year CDS spread			
	Mean	Max	Min	Std
Verizon	68.6144	169.3000	18.6000	29.6478
Boeing	92.9535	322.0000	15.2000	67.3197
Caterpillar	123.1250	504.9100	33.4000	101.0075
Chevron	68.6143	129.0000	20.1000	29.7738
Coca-cola	36.2504	84.5000	17.8000	13.8985
Walt Disney	42.8312	108.5000	19.8000	18.4209
E.I. du Pont	45.4038	207.0000	16.0000	34.9434
Exxon	31.5696	99.4000	12.0000	19.2140
Home Depot	111.2713	330.3000	31.0650	71.5890
Intel	45.1969	83.6060	22.2300	24.5180
Johnson&Johnson	31.7979	70.6000	10.8000	13.8626
Mcdonald	30.3598	63.0000	11.7100	12.0808
3M	40.2012	113.7000	14.6250	24.2850
Procter&Gamble	52.3325	147.1000	19.4000	32.4460
AT&T	38.1561	107.3000	12.4000	17.8618
United Health	118.0969	416.6250	39.1090	84.4500
United Technologies	46.1059	118.3000	19.6100	22.5466
Wal-Mart	47.9782	120.6000	21.7000	25.4582
Microsoft	25.5980	85.0000	7.8104	8.2000
Cisco	49.7668	143.7000	20.4000	23.8078

Note: This table reports the summary statistics of 5-year CDS spreads for 20 Down Jones Firms from 02/01/2008-31/12/2013. The numbers are expressed in basis point.

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Table 3: SVJ structural Model Estimation Results for 20 Dow Jones Companies

Company name		μ	θ	κ	σ_V	λ	$\overline{J}$	σ_J	δ	F	$MLMLH$
	Mean	0.0046	0.0167	12.578	0.1996	0.0032	0.0012	0.1274	0.0027	1.0945×10^5	
Verizon	0.05 Qtl	-0.0797	0.0129	8.437	0.0998	0.0008	0.0009	0.0975	0.0011	8.9570×10^4	946.72
	0.95 Qtl	0.1176	0.0210	18.256	0.2765	0.0051	0.0033	0.2986	0.0042	1.3157×10^5	
	Mean	0.0277	0.0318	10.276	0.1975	0.0057	0.0063	0.1587	0.0017	5.1579×10^4	
Boeing	0.05 Qtl	-0.0847	0.0279	8.723	0.1135	0.0023	0.0047	0.0825	0.0003	4.6832×10^4	925.33
	0.95 Qtl	0.1466	0.0356	16.759	0.2872	0.0086	0.0105	0.2574	0.0034	5.7229×10^4	
	Mean	0.0810	0.0378	11.098	0.4391	0.0015	0.0027	0.0129	0.0022	4.7439×10^4	
Caterpillar	0.05 Qtl	-0.0498	0.0349	4.675	0.1957	0.0009	0.0012	0.0095	0.0011	4.3608×10^4	879.61
	0.95 Qtl	0.2416	0.0397	19.884	0.6332	0.0026	0.0032	0.0153	0.0043	5.0305×10^4	
	Mean	0.0279	0.0396	15.987	0.4331	0.0025	0.0013	0.0228	0.0048	7.1009×10^4	
Chevron	0.05 Qtl	-0.1322	0.0382	6.778	0.2098	0.0014	0.0008	0.0125	0.0045	6.9327×10^4	895.47
	0.95 Qtl	0.2005	0.0400	20.912	0.6776	0.0037	0.0024	0.0326	0.0050	7.1918×10^4	
	Mean	0.0667	0.0377	10.224	0.5331	0.0056	0.0436	0.0275	0.0038	2.2054×10^5	
Coca-Cola	0.05 Qtl	-0.0810	0.0357	3.987	0.3207	0.0031	0.0258	0.0156	0.0030	2.0646×10^5	918.94
	0.95 Qtl	0.1903	0.0399	18.090	0.6652	0.0072	0.0627	0.0305	0.0046	2.3139×10^5	
	Mean	0.0378	0.0395	17.223	0.3341	0.0065	0.0026	0.3287	0.0048	2.7358×10^4	
Walt Disney	0.05 Qtl	-0.1059	0.0389	9.087	0.1126	0.0042	0.0011	0.2076	0.0043	2.6797×10^4	874.56
	0.95 Qtl	0.1793	0.0400	23.998	0.5430	0.0081	0.5127	0.3923	0.0050	2.7681×10^4	
	Mean	0.0562	0.0380	10.876	0.4219	0.0041	0.0049	0.1657	0.0039	2.9429×10^4	
E.I. du Pont	0.05 Qtl	-0.0929	0.0358	2.993	0.2325	0.0036	0.0035	0.0983	0.0029	2.7588×10^4	894.30
	0.95 Qtl	0.2131	0.0398	16.095	0.5098	0.0052	0.0057	0.2014	0.0048	3.0414×10^4	
	Mean	-0.0645	0.0396	15.908	0.3348	0.0074	0.0021	0.2573	0.0049	1.1420×10^5	
Exxon	0.05 Qtl	-0.1853	0.0382	5.214	0.1980	0.0061	0.0014	0.1786	0.0046	1.0948×10^5	926.19
	0.95 Qtl	0.1007	0.0400	22.987	0.5231	0.0089	0.0033	0.3326	0.0050	1.1722×10^5	
	Mean	0.0646	0.0395	13.776	0.2241	0.0025	0.0014	0.3659	0.0046	2.3060×10^4	
Home Depot	0.05 Qtl	-0.0826	0.0389	5.786	0.1087	0.0017	0.0008	0.2219	0.0040	2.2596×10^4	931.48
	0.95 Qtl	0.2016	0.0400	20.997	0.3066	0.0034	0.0020	0.4023	0.0050	2.3362×10^4	
	Mean	0.0559	0.0333	12.989	0.3891	0.0014	0.0026	0.2129	0.0017	8.0034×10^4	
Intel	0.05 Qtl	-0.0900	0.0311	5.887	0.2085	0.0007	0.0013	0.1186	0.0005	7.3835×10^4	886.43
	0.95 Qtl	0.1974	0.0360	17.224	0.5098	0.0025	0.0034	0.3234	0.0030	8.4765×10^4	

	Mean	-0.0326	0.0231	18.765	0.3321	0.0025	0.0041	0.2235	0.0036	4.1332×10^4	
Johnson & Johnson	0.05 Qtl	-0.1268	0.0211	10.228	0.2653	0.0014	0.0032	0.1764	0.0027	3.6794×10^4	898.73
	0.95 Qtl	0.0809	0.0257	29.876	0.5208	0.0033	0.0054	0.3546	0.0048	4.3938×10^4	
	Mean	0.1063	0.0319	12.989	0.3321	0.0041	0.0026	0.4079	0.0045	1.5003×10^4	
Mcdonald	0.05 Qtl	-0.0259	0.0295	7.232	0.2987	0.0021	0.0018	0.2764	0.0040	1.3413×10^4	944.31
	0.95 Qtl	0.2459	0.0347	19.887	0.5321	0.0054	0.0039	0.5123	0.0049	1.6026×10^4	
	Mean	0.0361	0.0389	10.998	0.4217	0.0028	0.0016	0.1513	0.0047	1.3478×10^4	
3M	0.05 Qtl	-0.1092	0.0291	3.885	0.2238	0.0010	0.0009	0.1024	0.0042	1.2551×10^4	821.25
	0.95 Qtl	0.1642	0.0452	16.989	0.5356	0.0032	0.0025	0.2287	0.0050	1.3939×10^4	
	Mean	-0.0290	0.0249	17.098	0.3432	0.0037	0.0025	0.2671	0.0043	6.1996×10^4	
Procter & Gamble	0.05 Qtl	-0.1583	0.0226	10.291	0.2109	0.0022	0.0018	0.1983	0.0037	5.3287×10^4	850.92
	0.95 Qtl	0.1010	0.0281	25.439	0.4342	0.0043	0.0031	0.3085	0.0049	6.9547×10^4	
	Mean	-0.0473	0.0285	11.223	0.3238	0.0037	0.0024	0.2026	0.0038	1.1040×10^5	
AT/T	0.05 Qtl	-0.1775	0.0253	4.998	0.2901	0.0023	0.0012	0.1514	0.0024	1.0273×10^5	864.38
	0.95 Qtl	0.0940	0.0319	16.289	0.5529	0.0042	0.0033	0.3837	0.0046	1.2076×10^5	
	Mean	0.0430	0.0395	13.879	0.3906	0.0015	0.0034	0.2627	0.0046	3.5056×10^4	
United Health	0.05 Qtl	-0.0703	0.0372	7.9981	0.2176	0.0009	0.0023	0.1018	0.0038	3.4302×10^4	795.41
	0.95 Qtl	0.1611	0.0432	21.879	0.4432	0.0021	0.0045	0.3132	0.0049	3.5430×10^4	
	Mean	0.0273	0.0376	8.2351	0.1198	0.0012	0.0034	0.1517	0.0036	3.2973×10^4	
United Technologies	0.05 Qtl	-0.1134	0.0321	6.7093	0.0981	0.0008	0.0021	0.1089	0.0023	3.1213×10^4	897.66
	0.95 Qtl	0.1905	0.0438	10.2347	0.2865	0.0021	0.0040	0.2286	0.0048	3.4259×10^4	
	Mean	0.0554	0.0230	12.887	0.3376	0.0014	0.0023	0.1587	0.0046	8.2534×10^4	
Wal-Mart	0.05 Qtl	-0.0440	0.0209	5.679	0.1309	0.0007	0.0015	0.1015	0.0042	7.7116×10^4	823.57
	0.95 Qtl	0.1750	0.0254	19.824	0.5487	0.0025	0.3231	0.2028	0.0050	8.7963×10^4	
	Mean	-0.0302	0.0398	15.884	0.5498	0.0045	0.0023	0.1614	0.0049	3.7567×10^4	
Microsoft	0.05 Qtl	-0.1652	0.0352	9.761	0.2231	0.0033	0.0015	0.1012	0.0032	3.6742×10^4	897.43
	0.95 Qtl	0.0894	0.0400	21.325	0.7678	0.0052	0.0037	0.2829	0.0057	3.8314×10^4	
	Mean	-0.0572	0.0398	14.989	0.3241	0.0012	0.0037	0.2124	0.0050	2.9299×10^4	
Cisco	0.05 Qtl	-0.1983	0.0352	10.225	0.2256	0.0008	0.0012	0.1215	0.0049	2.9010×10^4	803.42
	0.95 Qtl	0.0669	0.0457	20.975	0.5098	0.0023	0.0041	0.3217	0.0065	2.9445×10^4	

Note: This table reports the parameter estimates of the SVJ model at the final date T with the first 993 equity value observations using MRM for 20 Dow Jones firms. In estimation, we set the number of state and parameter particles are respectively 500 and 1000. The priors are $\mu \sim N(0, 005)$, $(\theta, \kappa, \sigma_V, \lambda, \overline{J}, \sigma_J, \delta) \sim U[(0.001^2, 0, 1\times10^5, 0.001, -0.01, 0.01, 1\times10^6), (0.2^2, 20, 2, 0.01, -0.01, 0.1, 0.05)]$.

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Table 4: 5-year CDS Spread Estimation Results for 20 Dow Jones Companies

	Panel A: 02/01/2008-30/12/2011									
	Merton model		Merton model*		SV model*		SV model		SVJ model	
Company Name	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
Verizon	-52.3537	54.3911	-49.8782	52.8986	-48.7274	51.9986	-45.8976	48.1253	-44.8786	47.3578
Boeing	-33.6025	42.8716	-31.8976	40.2758	-32.0986	40.1764	-29.8784	38.2189	-27.2135	37.1865
Caterpillar	-22.6754	45.2125	-20.8896	43.1845	-21.9456	42.8976	-19.8765	40.9876	-18.9765	39.1236
Chevron	-37.0361	42.8225	-35.8976	40.2891	-36.1215	40.1876	-33.1893	38.2935	-32.8976	37.6541
Coca-cola	-32.8873	46.9896	-30.1819	44.8976	-31.8765	43.5462	-28.7673	40.8972	-27.1789	39.2373
Walt Disney	-31.2267	40.1258	-29.7865	38.1237	-29.8764	38.5643	-26.1798	35.7892	-24.7895	34.1246
E.I.du Pont	-32.1876	38.0160	-29.8973	36.8965	-28.9764	36.1214	-26.7893	35.1287	-25.3893	33.2781
Exxon	-20.7865	29.7671	-18.7432	27.1893	19.2876	28.0981	-16.2755	23.8971	-15.0987	22.9109
Home Depot	-80.2156	94.2896	-77.1985	92.8912	-78.1256	91.2859	-75.8941	89.7667	-75.0915	89.0974
Intel	-35.7871	46.7924	-33.8696	44.8952	-32.9761	44.5642	-30.5562	40.8699	-29.7851	39.0876
Johnson&Johnson	-20.8953	34.8791	-18.7581	32.9774	-18.0876	31.8908	-15.8916	28.9075	-14.9872	27.0981
Mcdonald	-27.4341	29.2104	-25.9796	27.8915	-26.0987	26.9861	-22.8914	23.9194	-21.9532	22.6539
3M	-38.1276	44.3381	-36.9806	43.5815	-36.7424	42.8974	-35.8971	39.8017	-34.0911	38.0945
Procter&Gamble	-52.1764	65.8932	-50.1677	63.8078	-49.8608	62.1917	-45.9751	59.0137	-44.0898	58.0925
AT&T	-63.2178	74.3872	-61.8976	72.9061	-61.9895	72.6543	-58.9871	69.0832	-57.0984	68.1256
United Health	-90.2325	101.8786	-87.1437	99.0861	-87.3536	98.7961	-85.9187	95.2426	-84.8913	94.5759
United Technologies	-37.6529	45.7893	-35.0861	43.0877	-34.9872	42.9895	-32.9861	39.0853	-31.2678	38.0954
Wal-Mart	-45.8972	52.8974	-43.6783	50.0913	-43.0981	49.8125	-40.9916	46.0871	-39.6754	45.5672
Microsoft	-20.1974	25.8761	-17.4564	23.9086	-17.0983	23.0546	-15.0897	20.0952	-14.2576	19.2325
Cisco	-42.7935	54.8964	-41.8971	53.0892	-40.9897	52.9891	-35.8908	48.0872	-34.9087	47.5415

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Panel B: 02/01/2008-30/12/2009										
	Merton model		Merton model*		SV model*		SV model		SVJ model	
Company Name	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
Verizon	-54.1967	57.8972	-51.7865	53.9801	-51.9861	53.5609	-45.9086	49.0821	-43.2354	46.3576
Boeing	-35.9261	44.8921	-31.9082	40.9852	-31.5476	40.6765	-26.7786	35.8987	-23.8901	33.0981
Caterpillar	-24.7893	46.9871	-21.8976	42.9025	-21.5802	42.4341	-17.8061	38.9006	-15.8661	35.9081
Chevron	-35.1974	44.8975	-32.6976	41.0905	-32.4531	41.2416	-29.9861	36.0871	-26.9087	34.9081
Coca-cola	-33.2578	48.9072	-30.8861	45.7656	-29.0854	44.9086	-26.8799	39.0751	-24.0976	37.0908
Walt Disney	-32.8976	42.8975	-29.0875	38.0817	-28.9082	37.8981	-24.0835	34.0926	-22.0061	32.0866
E.I.du Pont	-34.5092	40.1984	-31.0907	36.3254	-30.9895	36.0278	-26.9895	33.9086	-23.8721	31.0984
Exxon	-22.7896	31.8963	-19.7864	28.9086	-19.8076	28.7854	-16.9982	25.0807	-14.0873	23.8956
Home Depot	-82.3672	96.1872	-79.8654	93.9086	-79.8753	93.7654	-76.8125	89.3241	-73.9852	87.6635
Intel	-37.0981	48.9076	-33.0986	45.7516	-33.1567	45.3479	-31.0086	42.7872	-29.9809	39.0805
Johnson&Johnson	-21.9086	36.0783	-18.7756	33.8785	-18.6523	33.7674	-15.8906	31.9077	-13.9765	28.7673
Mcdonald	-29.4956	31.9090	-25.0875	29.6797	-25.7872	29.8754	-23.4547	26.8784	-21.0098	23.4569
3M	-40.9892	46.1214	-35.4648	43.2215	-35.4647	43.1258	-33.4468	40.9896	-31.9895	37.0965
Procter&Gamble	-54.6710	67.0982	-50.1135	64.3437	-50.2326	64.3539	-47.2429	62.1154	-45.4273	60.9894
AT&T	-65.0102	75.9035	-62.1157	73.2578	-62.6754	73.5452	-59.8783	68.1195	-57.7672	65.7892
United Health	-92.0805	103.4547	-89.7674	99.3246	-89.8923	99.5654	-85.4432	95.0874	-83.1257	92.7759
United Technologies	-39.0201	47.2356	-36.1278	44.5371	-36.3260	44.6862	-33.7981	41.0805	-31.8974	39.7763
Wal-Mart	-47.0831	54.0756	-43.9987	52.9063	-43.8751	52.5654	-41.9987	48.0906	-39.0852	45.7763
Microsoft	-22.7673	28.0974	-19.8784	25.8983	-19.5421	25.5437	-15.9086	23.0667	-14.9621	20.7764
Cisco	-44.9087	56.9823	-41.0064	53.0986	-41.2326	53.1215	-38.0906	49.8982	-35.0985	46.1214

Note: This table reports the bias and RMSE of the estimated 5-year CDS spreads from the standard Merton model, the Merton model with rolling samples (Merton model*), the SV model with a fixed volatility state variable (SV model*), the standard SV model and the SVJ model for 20 Dow Jones firms. Panel A presents the results of the whole estimation period, and Panel B presents the results for the crisis subsample period. The numbers are expressed in basis point.

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Table 5: 5-year CDS Spread Prediction Results for 20 Dow Jones Companies

	Panel A: One step ahead									
	Merton model		Merton model*		SV model*		SV model		SVJ model	
Company Name	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
Verizon	-30.9876	37.8921	-28.9901	35.1716	-28.6752	35.2765	-25.4647	32.9086	-23.8761	30.7673
Boeing	-20.9897	27.8015	-18.3437	25.3291	-18.2276	25.4743	-15.2329	23.8907	-13.4479	21.0908
Caterpillar	-17.0071	25.0765	-15.8633	23.9096	-15.6239	23.7674	-13.8976	20.9563	-11.6509	17.7865
Chevron	-17.9140	18.9626	-15.8983	16.2426	-15.6658	16.1217	-13.0903	14.0114	-11.7673	12.6532
Coca-cola	-23.5782	29.8784	-20.7654	26.5543	-20.5641	26.3987	-18.7675	23.8064	-16.8782	21.0706
Walt Disney	-19.9983	25.0985	-17.6662	23.8785	-17.2326	23.4549	-15.4438	20.7672	-13.2986	18.3638
E.I.du Pont	-18.9622	20.0491	-16.0876	18.1267	-16.3436	18.4268	-14.0654	14.5657	-13.3236	13.8785
Exxon	-15.4467	19.0876	-13.3678	17.6564	-13.4721	17.3439	-11.7674	15.3238	-10.8784	13.2987
Home Depot	-50.9873	59.6564	-48.7652	57.0073	-48.5657	56.9893	-45.7862	53.7865	-45.2328	52.8897
Intel	-20.8965	29.3437	-17.9972	27.8075	-17.6568	27.4589	-15.9972	24.1316	-13.4786	23.9896
Johnson&Johnson	-17.0983	24.6512	-15.0467	22.6439	-15.3231	22.9873	-13.5629	19.9836	-12.9897	18.7654
Mcdonald's	-13.1351	13.6534	-12.0326	12.9897	-12.1678	12.5458	-9.8832	9.7675	-9.5451	9.2108
3M	-25.8976	30.9871	-23.6754	28.7673	-23.1617	28.6561	-20.8876	24.3937	-18.5453	22.8784
Procter&Gamble	-42.7765	49.0971	-39.9897	47.2137	-39.6764	47.0983	-35.1216	43.7685	-34.9981	43.0256
AT&T	-43.2267	50.6562	-40.9871	47.6562	-40.6564	47.2326	-37.6652	43.0061	-37.1215	42.6754
United Health	-80.6675	85.1216	-78.9763	83.2786	-78.5467	83.2521	-74.2899	80.9294	-72.7671	79.6536
United Technologies	-25.6671	30.6128	-23.4686	28.6564	-23.7865	28.4327	-20.8975	24.3638	-19.8786	23.9897
Wal-Mart	-20.8651	34.7869	-18.7675	31.2786	-18.5654	31.0908	-15.7875	28.7674	-13.9725	27.5432
Microsoft	-19.8054	22.1187	-17.9795	20.7673	-17.6534	20.5459	-15.3276	17.6563	-14.8765	16.9114
Cisco	-25.7655	29.8076	-23.7654	27.8685	-23.4548	27.9871	-20.7642	24.7632	-19.8785	23.9896

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Panel B: five-step-ahead										
	Merton model		Merton model*		SV model*		SV model		SVJ model	
Company Name	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
Verizon	-32.7765	38.9967	-30.9987	36.5643	-30.6752	36.2765	-26.4879	34.7876	-26.1145	31.9802
Boeing	-24.8962	29.2897	-22.0987	27.1103	-22.7675	27.1248	-18.6547	24.7375	-17.0102	21.8137
Caterpillar	-19.6368	28.4645	-17.1287	26.3439	-17.6239	26.0785	-15.7674	23.7674	-14.9981	20.9563
Chevron	-20.1318	23.4547	-18.7765	20.3736	-18.9374	20.1718	-15.1617	18.4347	-14.9896	13.2234
Coca-cola	-25.6783	31.7675	-23.9791	29.0807	-23.6238	26.3987	-17.2328	24.1176	-16.9098	22.6761
Walt Disney	-21.7675	27.1413	-19.1142	25.0578	-19.0327	25.0436	-16.0325	23.7674	-14.3761	21.4983
E.I.du Pont	-35.0637	40.1137	-33.6564	38.3236	-33.6568	38.4805	-30.1162	36.1318	-29.0705	33.9986
Exxon	-18.0782	21.3427	-16.0548	19.7674	-16.2326	19.5453	-14.0675	17.1132	-13.9896	14.1129
Home Depot	-48.2127	60.8972	-47.1215	58.7863	-47.2128	58.7673	-44.1217	55.5674	-43.3768	52.67653
Intel	-24.9076	32.5645	-22.8784	30.7674	-22.7673	30.3739	-19.3438	28.8975	-17.3236	25.1784
Johnson&Johnson	-19.5654	26.8973	-17.2328	24.6893	-17.5451	24.5857	-15.1124	22.6763	-14.6567	20.8986
McDonald's	-15.6567	16.4678	-13.2573	14.7873	-13.1897	14.5458	-11.7673	12.4749	-11.5451	10.2108
3M	-29.6765	33.7674	-26.4542	29.8943	-26.3231	29.7674	-23.1251	27.1367	-22.4328	26.8785
Procter&Gamble	-45.9097	53.5551	-39.9897	47.2137	-39.6764	47.0983	-35.1216	43.7685	-34.9981	41.0256
AT&T	-45.5672	53.4849	-43.7135	49.9895	-43.4542	49.1315	-39.0403	45.1218	-39.5654	42.8785
United Health	-82.3436	87.3589	-80.8984	85.8973	-80.3231	85.4348	-76.3235	82.7876	-76.0902	79.9536
United Technologies	-27.7873	34.5631	-25.7875	32.7865	-25.4342	32.5327	-23.7761	29.8783	-22.8731	27.0982
Wal-Mart	-23.1457	36.8123	-20.6563	34.5682	-20.5351	34.7673	-18.4342	31.3432	-17.5451	28.5356
Microsoft	-21.9876	25.3245	-20.7675	23.8973	-20.0951	23.5564	-19.5456	20.7675	-18.9084	17.1211
Cisco	-28.9082	30.7675	-27.8907	29.9861	-27.4548	29.3210	-24.3765	25.3231	-22.8973	22.8785

Note: This table reports the bias and RMSE of the predicted 5-year CDS spreads from the standard Merton model, the Merton model with rolling samples (Merton model*), the SV model with a fixed volatility state variable (SV model*), the standard SV model and the SVJ model for 20 Dow Jones firms. Panel A presents the results for one-step-ahead predictions, and Panel B presents the results for five-step-ahead predictions. The numbers are expressed in basis point.

Table 6: The summary statistics of the regression based model comparison results: Panel A

	$CDS_t = \beta_0 + C\hat{D}S_t + \varepsilon_t$									
	Merton model		Merton model*		SV model*		SV model		SVJ model	
	β_0	R^2	β_0	R^2	β_0	R^2	β_0	R^2	β_0	R^2
	One step ahead									
Mean	27.5836	0.5135	25.4217	0.5237	25.2510	0.5239	22.6850	0.5396	21.6263	0.5469
Median	20.9431	0.5089	18.5556	0.5196	18.3965	0.51925	15.89235	0.5394	14.7219	0.5432
10 Percentile	16.8510	0.4413	14.8788	0.4633	15.1380	0.4594	12.9580	0.4797	12.5784	0.4872
90 Percentile	44.0027	0.5874	41.7649	0.5928	41.4473	0.5947	38.4773	0.6056	37.9327	0.6145
Min	13.1351	0.4123	12.0326	0.4234	12.1678	0.4245	9.8832	0.4306	9.5451	0.4389
Max	80.6675	0.5982	78.9763	0.6075	78.5467	0.6124	74.2899	0.6286	72.7671	0.6315
	Five step ahead									
Mean	30.5848	0.4887	28.4227	0.5091	28.3280	0.5082	25.1804	0.5243	24.4085	0.5341
Median	25.2929	0.4913	23.4287	0.5091	23.1956	0.5092	19.4447	0.5215	18.2267	0.5295
10 Percentile	19.4166	0.4252	17.02131	0.4488	17.4138	0.4466	15.0079	0.4590	14.3374	0.4681
90 Percentile	46.1400	0.5547	44.0543	0.5774	43.8300	0.5771	39.5484	0.6005	39.9465	0.6077
Min	15.6567	0.3974	13.2573	0.4044	13.1897	0.4056	11.7673	0.4127	11.5451	0.4285
Max	82.3436	0.5754	80.8984	0.5923	80.3231	0.5924	76.3235	0.6082	75.5902	0.6214

Note: This table reports the summary statistics of the regression based test results on the one-step-ahead and five-step-ahead model predicted credit spreads for 20 Dow Jones firms. The regression is restricted by setting $\beta_1 = 1$. Merton model* denotes the Merton model with rollowing samples, and SV model* denotes the artificial SV model with the volatility state variable being fixed at its stationary level.

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Table 7: The summary statistics of the regression based model comparison results: Panel B

	$CDS_t = \beta_0 + \beta_1 C\hat{D}S_t + \varepsilon_t$														
	Merton model			Merton model*			SV model*			SV model			SVJ model		
	β_0	β_1	R^2	β_0	β_1	R^2	β_0	β_1	R^2	β_0	β_1	R^2	β_0	β_1	R^2
	One step ahead														
Mean	24.01	8.14	0.44	20.29	7.15	0.47	20.27	6.99	0.47	17.89	6.05	0.51	16.36	5.49	0.53
Median	18.05	7.53	0.43	14.73	6.50	0.47	14.57	6.63	0.47	11.97	5.55	0.51	10.37	5.35	0.52
10 Percentile	14.50	5.23	0.38	10.80	4.75	0.40	10.53	4.71	0.41	8.77	3.68	0.43	7.32	3.21	0.47
90 Percentile	41.36	12.53	0.52	36.39	10.26	0.55	36.42	10.12	0.55	34.38	8.98	0.59	32.16	8.041	0.60
Min	9.34	3.78	0.35	7.83	3.32	0.37	8.09	3.23	0.37	7.34	2.82	0.40	7.01	2.49	0.42
Max	75.46	14.27	0.53	70.11	12.89	0.57	70.33	10.23	0.57	65.72	9.04	0.61	63.42	8.55	0.62
	Five step ahead														
Mean	26.73	8.93	0.41	22.77	7.82	0.45	22.58	7.54	0.45	19.77	6.48	0.49	17.78	6.22	0.51
Median	22.66	8.50	0.40	19.44	7.52	0.45	18.56	7.63	0.45	15.23	6.31	0.49	13.29	6.10	0.50
10 Percentile	15.81	6.12	0.35	10.97	5.48	0.38	11.07	5.81	0.39	9.74	4.69	0.42	8.17	4.50	0.45
90 Percentile	41.56	13.13	0.48	36.20	10.98	0.51	36.22	10.12	0.51	31.22	8.24	0.55	29.89	7.98	0.58
Min	12.19	5.55	0.33	9.25	4.56	0.36	10.98	4.23	0.36	8.34	4.08	0.39	7.89	3.98	0.40
Max	76.02	15.98	0.51	70.89	11.34	0.54	71.22	10.23	0.54	65.12	8.56	0.58	62.11	8.02	0.63

Note: This table reports the summary statistics of the regression based test results on the one-step-ahead and five-step-ahead model predicted credit spreads without any restriction for 20 Dow Jones firms. Merton model* denotes the Merton model with rollowing samples, and SV model* denotes the artificial SV model with the volatility state variable being fixed at its stationary level.

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Table 8: The summary statistics of the regression based model comparison results: Panel C

$CDS_t = \beta_0 + \beta_1 \hat{CDS}_{Merton,t} + \beta_2 \hat{CDS}_{SV-Merton,t} + \varepsilon_t$				
	β_0	β_1	β_2	R^2
	One step ahead			
Mean	14.2939	6.0669	1.7113	0.5197
Median	14.2939	5.2881	0.9051	0.5165
10 Percentile	11.2582	3.0904	0.4876	0.4357
90 Percentile	37.7826	9.9901	3.3222	0.6019
Min	7.3235	2.8091	0.3321	0.4172
Max	72.0824	11.0977	4.5658	0.6124
	Five step ahead			
Mean	15.5788	4.9863	1.9581	0.4974
Median	11.5587	5.0526	2.0399	0.5007
10 Percentile	7.0305	4.2305	0.8744	0.4197
90 Percentile	26.9804	6.1725	3.4238	0.5613
Min	5.0437	3.2126	0.5467	0.4022
Max	53.4872	7.0623	3.4549	0.5809

Note: This table reports the summary statistics of the incremental information test results between the Merton model and SV model in credit spread prediction for 20 Dow Jones firms.

Table 9: The summary statistics of the regression based model comparison results: Panel D

$CDS_t = \beta_0 + \beta_1 \hat{CDS}_{SV,t} + \beta_2 \hat{CDS}_{SVJ-SV,t} + \varepsilon_t$				
	β_0	β_1	β_2	R^2
	One step ahead			
Mean	14.6655	5.7722	1.4118	0.5332
Median	9.4725	5.5107	1.1070	0.5311
10 Percentile	6.9806	4.2207	0.0867	0.4755
90 Percentile	30.0073	8.2276	2.8058	0.6118
Min	6.1132	4.0526	0.0421	0.4106
Max	52.3127	8.9122	4.8792	0.6287
	Five step ahead			
Mean	13.7844	4.3585	1.2768	0.5094
Median	8.9481	3.2597	1.0397	0.5059
10 Percentile	6.2509	1.8622	0.7556	0.4464
90 Percentile	30.2507	8.7824	1.9255	
Min	2.2215	1.2324	0.0578	0.4021
Max	58.3348	10.7681	3.2107	0.6027

Note: This table reports the summary statistics of the incremental information test results between the SV model and the SVJ model in credit spread prediction for 20 Dow Jones firms.

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Table 10: SVJ structural Model Estimation Results for 200 CRSP firms

Company name	μ	θ	κ	σ_V	λ	$\overline{J}$	σ_J	δ	F	$MLMLH$
Mean	0.0046	0.0382	14.9235	0.4231	0.0032	0.0029	0.3274	0.0058	1.6542×10^5	950.4421
Median	0.0039	0.0314	12.8976	0.3325	0.0030	0.0025	0.2983	0.0044	1.5253×10^5	922.3836
10 Percentile	-0.0532	0.0127	8.9923	0.1381	0.0009	0.0009	0.1124	0.0023	9.2327×10^4	901.2945
90 Percentile	0.0058	0.0503	17.0342	0.5247	0.0043	0.0051	0.5672	0.0079	2.8789×10^5	980.8632
Min	-0.0038	0.0026	5.6761	0.0762	0.0001	0.0002	0.0573	0.0014	1.2327×10^4	876.5331
Max	0.0084	0.0729	20.9894	0.8761	0.0092	0.0074	0.7382	0.0093	3.4542×10^5	1009.2384

Note: This table reports the summary statistics of the parameter estimates of the SVJ model at the final date T with the first 993 equity value observations using MRM for 200 CRSP firms. In estimation, we set the number of state and parameter particles are respectively 500 and 1000. The priors are $\mu \sim N(0, 005)$, $(\theta, \kappa, \sigma_V, \lambda, \overline{J}, \sigma_J, \delta) \sim U[(0.001^2, 0, 1\times10^5, 0.001, -0.01, 0.01, 1\times10^6), (0.2^2, 20, 2, 0.01, -0.01, 0.1, 0.05)]$.

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Table 11: 5-year CDS Spread Prediction Results for 200 CRSP firms

	Merton model		Merton model*		SV model*		SV model		SVJ model	
Company Name	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
Panel A: One step ahead										
Mean	-40.1256	45.8765	-38.9092	42.0894	-38.5436	42.3307	-34.2321	38.8830	-32.0983	36.2579
Median	-33.1092	38.2984	-29.1582	35.0933	-29.2324	35.4226	-26.0986	30.1123	-24.1308	28.1137
10 Percentile	-13.2046	19.8124	-11.8633	16.7877	-11.0203	16.2341	-9.8123	14.8764	-8.4342	13.0629
90 Percentile	-63.9125	68.1001	-61.9929	66.1284	-61.3906	65.9082	-59.2566	62.0193	-57.1214	60.1897
Min	-10.2416	13.0206	-9.2353	11.0965	-9.5427	11.2571	-7.9863	9.0873	-6.2256	8.0974
Max	-57.9882	62.1264	-55.8763	60.0989	-55.1152	60.1217	-51.1896	57.2034	-49.8762	54.2231
Panel B: Five step ahead										
	Merton model		Merton model*		SV model*		SV model		SVJ model	
Company Name	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE
Mean	-45.2326	49.1174	-43.2008	47.0233	-43.2124	47.5762	-39.8762	42.7751	-37.1679	40.2903
Median	-40.1416	42.4676	-38.8567	40.3674	-38.6785	40.0913	-35.6349	35.1123	-34.2986	33.7632
10 Percentile	-18.2008	20.6754	-16.1119	18.3675	-16.3438	18.2046	-13.7382	15.2526	-11.3768	13.9087
90 Percentile	-70.9815	74.3665	-67.2967	72.0034	-67.3872	72.8760	-64.1353	67.8072	-62.0976	65.3321
Min	-13.0086	15.1567	-11.1156	13.8765	-11.2567	13.9624	-9.9886	11.1562	-9.7673	10.0972
Max	-80.1564	85.3561	-78.2073	83.02145	-78.1138	83.4542	-74.8614	79.0051	-72.1562	77.2238

Note: This table reports the bias and RMSE of 5-year CDS spread predictions for the 200 CRSP firms from the standard Merton model, the SV model with a fixed volatility state variable (SV model[a]) and the standard SV model(SV model[b]) for the last 498 days from January 3, 2012 to December 30, 2013. The numbers are expressed in basis point.

Table 12: The summary statistics of the regression based model comparison results: Panel A

	$CDS_t = \beta_0 + C\hat{D}S_t + \varepsilon_t$									
	Merton model		Merton model*		SV model*		SV model		SVJ model	
	β_0	R^2	β_0	R^2	β_0	R^2	β_0	R^2	β_0	R^2
	One step ahead									
Mean	40.1256	0.4765	38.9092	0.4982	38.5436	0.4967	35.2321	0.5283	32.0983	0.5391
Median	33.1092	0.4237	29.1582	0.4539	29.2324	0.4566	26.0986	0.4721	24.1308	0.5026
10 Percentile	13.2046	0.1344	16.7877	0.1507	16.2341	0.1523	14.8764	0.1892	13.0629	0.1904
90 Percentile	63.9125	0.6891	61.9929	0.7256	61.3906	0.7273	59.2566	0.7561	57.1214	0.7793
Min	10.2416	0.1084	9.1084	0.1106	9.5427	0.1123	7.9863	0.1346	6.2256	0.1521
Max	57.9882	0.7823	0.7832	0.8056	55.1152	0.8122	51.1896	0.8402	49.8762	0.8671
	Five step ahead									
Mean	45.2326	0.4382	43.2008	0.4511	43.2124	0.4527	39.8762	0.4831	37.1679	0.4952
Median	40.1416	0.3987	38.8567	0.4124	38.6785	0.4118	35.6349	0.4486	34.2986	0.4521
10 Percentile	18.2008	0.0829	16.1119	0.0106	16.3438	0.0112	13.7382	0.0143	11.3768	0.0155
90 Percentile	70.9815	0.5921	67.2967	0.6102	67.3872	0.6097	64.1353	0.6427	62.0976	0.6538
Min	13.0086	0.0633	11.1156	0.0862	11.2567	0.0897	9.9886	0.1084	9.7673	0.1215
Max	80.1564	0.7125	78.2073	0.7334	78.1138	0.7409	74.8614	0.7665	72.1562	0.7801

Note: This table reports the summary statistics of the results of regression based test on the one-step-ahead and five-step-ahead model predicted credit spreads for 200 CRSP firms. The regression is restricted by setting $\beta_1 = 1$. Merton model* denotes the Merton model with rollowing samples, and SV model* denotes the artificial SV model with the volatility state variable being fixed at its stationary level.

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Table 13: The summary statistics of the regression based model comparison results: Panel B

	$CDS_t = \beta_0 + \beta_1 \hat{CDS}_t + \varepsilon_t$														
	Merton model			Merton model*			SV model*			SV model			SVJ model		
	β_0	β_1	R^2	β_0	β_1	R^2	β_0	β_1	R^2	β_0	β_1	R^2	β_0	β_1	R^2
	One step ahead														
Mean	33.22	12.33	0.42	30.09	10.26	0.44	29.42	10.56	0.46	24.14	8.32	0.49	20.13	7.54	0.50
Median	28.77	10.82	0.39	25.89	9.22	0.42	24.76	9.87	0.42	21.09	8.33	0.45	23.12	7.65	0.47
10 Percentile	10.13	5.87	0.10	8.77	3.00	0.11	8.90	2.97	0.12	7.65	2.54	0.15	6.99	1.95	0.16
90 Percentile	58.90	15.77	0.60	54.32	14.20	0.63	53.89	14.98	0.61	50.91	12.65	0.63	48.01	10.43	0.65
Min	8.65	3.21	0.08	7.19	2.84	0.10	7.54	2.35	0.10	6.12	2.12	0.12	5.87	1.87	0.14
Max	60.98	13.22	0.69	56.22	12.76	0.67	56.10	11.03	0.69	52.76	9.09	0.73	50.88	8.64	0.75
	Five step ahead														
Mean	35.23	14.11	0.40	30.09	10.26	0.44	29.42	10.56	0.46	24.14	8.32	0.49	20.13	7.54	0.50
Median	30.12	12.33	0.37	25.89	9.22	0.42	24.76	9.87	0.42	21.09	8.33	0.45	23.12	7.65	0.47
10 Percentile	13.29	6.08	0.09	8.77	3.00	0.11	8.90	2.97	0.12	7.65	2.54	0.15	6.99	1.95	0.16
90 Percentile	60.98	16.21	0.58	54.32	14.20	0.63	53.89	14.98	0.61	50.91	12.65	0.63	48.01	10.43	0.65
Min	4.87	5.10	0.07	5.23	4.32	0.09	5.66	3.21	0.10	4.23	3.09	0.11	3.52	2.98	0.12
Max	70.93	16.23	0.67	66.04	14.53	0.68	66.11	11.03	0.69	63.80	10.98	0.71	60.32	9.87	0.72

Note: This table reports the summary statistics of the results of regression based test on the one-step-ahead and five-step-ahead model predicted credit spreads without any restriction for 200 CRSP firms. Merton model* denotes the Merton model with rollowing samples, and SV model* denotes the artificial SV model with the volatility state variable being fixed at its stationary level.

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Table 14: The summary statistics of the regression based model comparison results: Panel C

$CDS_t = \beta_0 + \beta_1 \hat{CDS}_{Merton,t} + \beta_2 \hat{CDS}_{SV-Merton,t} + \varepsilon_t$				
	β_0	β_1	β_2	R^2
	One step ahead			
Mean	12.1145	8.0932	1.3236	0.4651
Median	10.9087	7.2356	0.9872	0.4082
10 Percentile	5.2672	2.8973	0.2314	0.1986
90 Percentile	18.2980	11.0982	2.0452	0.5981
Max	20.1452	12.6753	2.8761	0.6972
Min	3.0487	1.7653	0.0982	0.1065
	Five step ahead			
Mean	13.0982	7.8341	0.9873	0.4562
Median	12.8076	8.0982	1.2096	0.3983
10 Percentile	6.2324	2.3567	0.4632	0.1703
90 Percentile	19.8763	12.8762	3.1014	0.5709
Max	21.0573	13.2876	3.1247	0.6608
Min	2.1784	1.5408	0.0876	0.0972

Note: This table reports the summary statistics of the results of incremental information test between the Merton model and SV model in credit spread prediction for 200 CRSP firms.

Table 15: The summary statistics of the regression based model comparison results: Panel D

$CDS_t = \beta_0 + \beta_1 \hat{CDS}_{SV,t} + \beta_2 \hat{CDS}_{SVJ-SV,t} + \varepsilon_t$				
	β_0	β_1	β_2	R^2
	One step ahead			
Mean	33.1256	13.0984	0.4956	
Median	28.0764	11.0763	0.4542	
10 Percentile	11.0982	5.8763	0.1561	
90 Percentile	56.7632	13.0465	0.6390	
Min	3.5427	4.3982	0.1195	
Max	69.8263	13.1247	0.7035	
	Five step ahead			
Mean	7.6521	0.4672	0.5038	
Median	19.0825	6.0528	0.4795	
10 Percentile	8.9073	2.0345	0.1632	
90 Percentile	52.0894	13.1215	0.6578	
Min	4.0897	2.6753	0.1196	
Max	61.0984	9.8723	0.7231	

Note: This table reports the summary statistics of the results of incremental information test between the SV model and the SVJ model in credit spread prediction for 200 CRSP firms.

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Figure 1: The average equity return and average 5-year CDS spread of 20 Dow Jones Firms

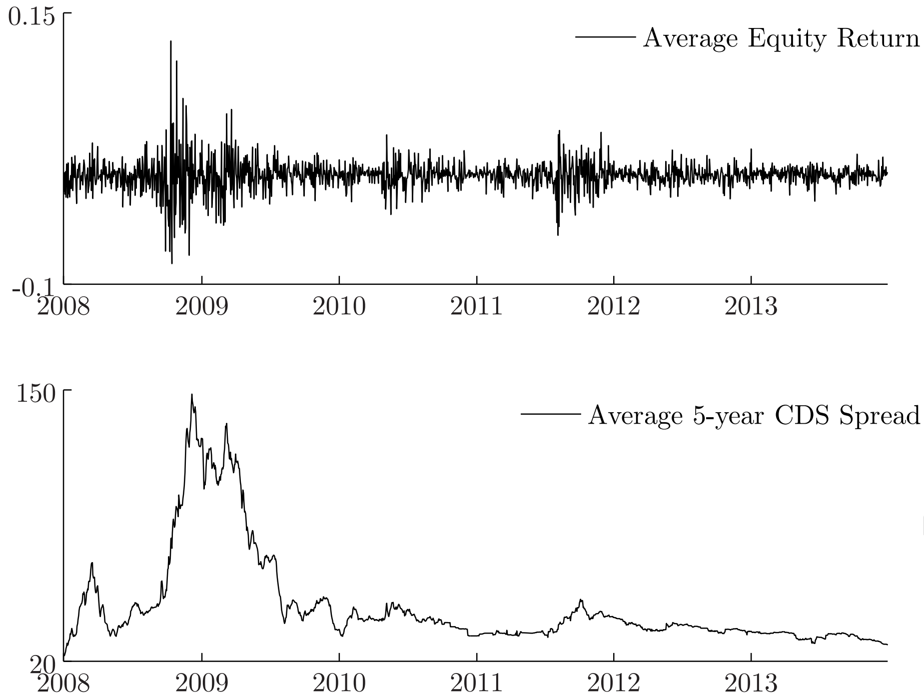

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Figure 2: Filtered average asset volatility from the SV structural model for 20 Down Jones firms

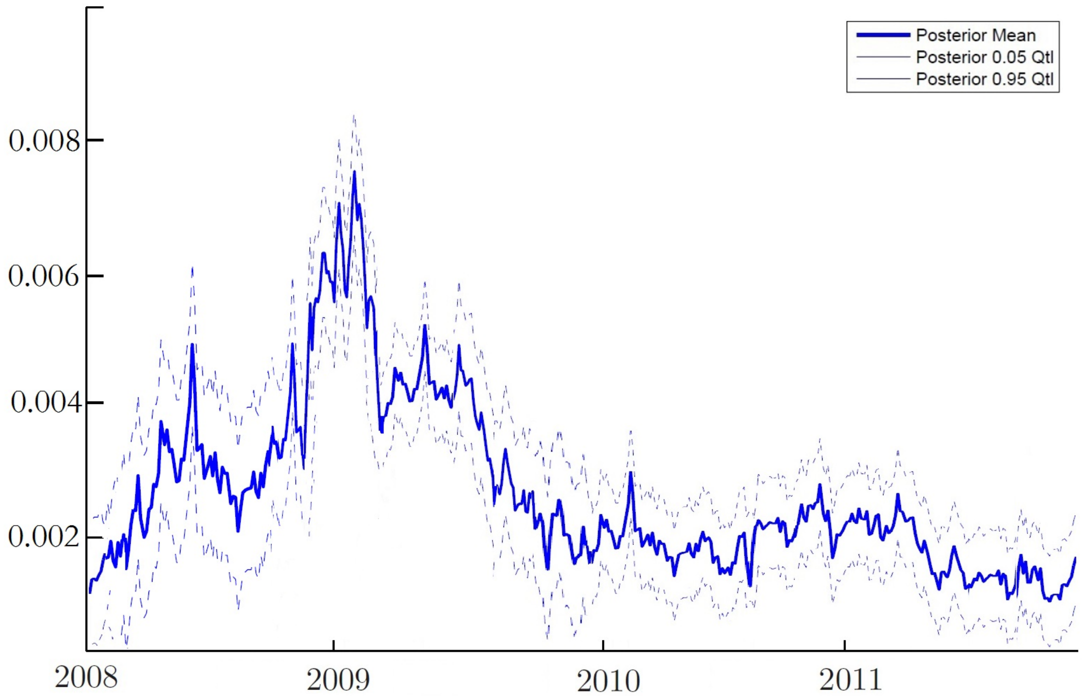

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Figure 3: Average Sequential log Bayes factors between SV structural model and Merton model for 20 Down Jones firms

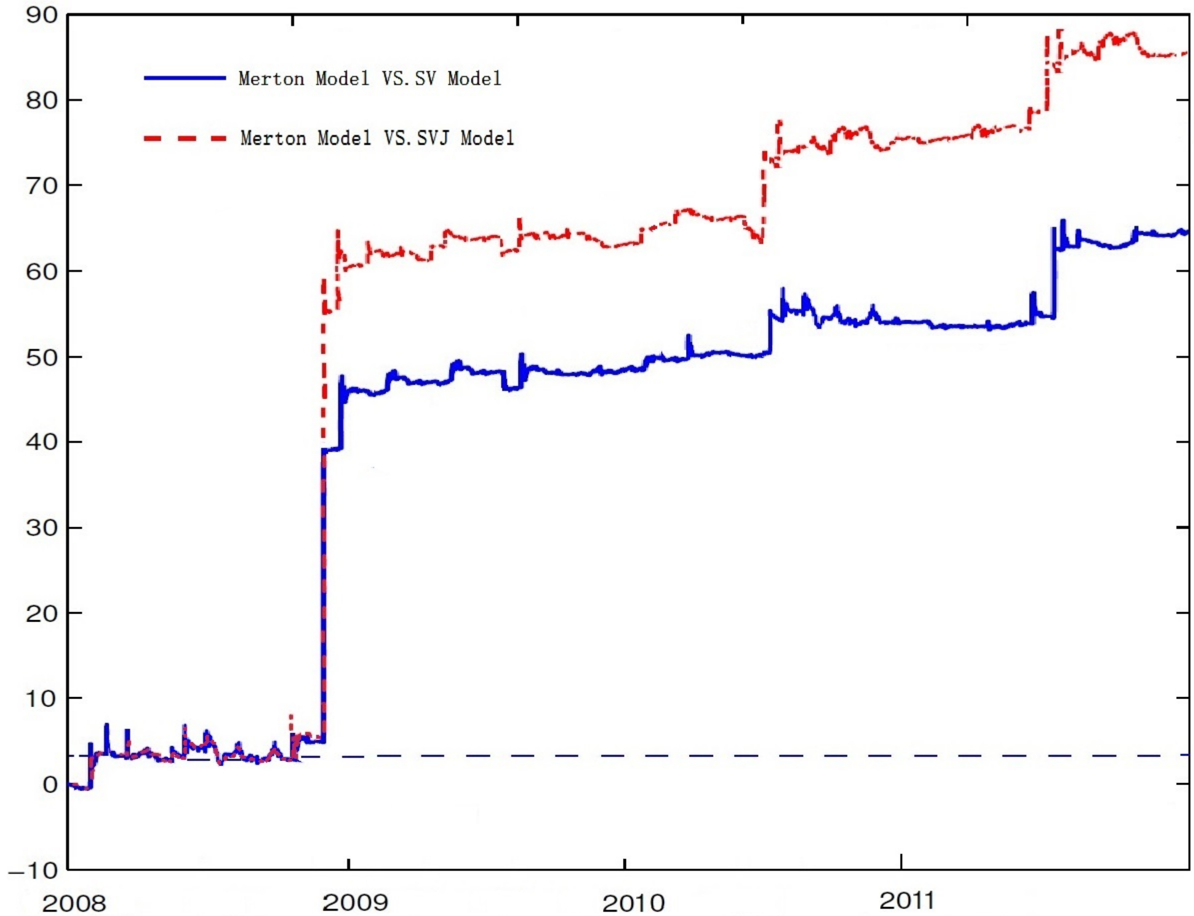

Figure 4: The predicted credit spreads V.S the actual 5-year CDS spreads for Verizon