No. 2014 [EN]

IMI Working Paper

The Volatility Morphology of Asset Value and the Credit Spread Puzzle: The Extension of Classical Merton Model

Xiao Hu, Xinming Tian and Kuitai Wang

INTERNATIONAL MONETARY INSTITUTE

For further information, please visit
http://www.imi.ruc.edu.cn/en/

Weibo

WeChat

IMI Working Paper No. 2014 [EN]

The Volatility Morphology of Asset Value and the Credit Spread Puzzle: The Extension of Classical Merton Model

By Xiao Hu, Xinming Tian and Kuitai Wang[1]

Abstract

Merton model has provided a classic theoretical framework for forecasting credit spreads. This paper extends Merton model by introducing morphology factor of asset value volatility in the model, and conducts empirical studies on the effect of volatility morphology factor on credit spreads in China's bond market both at the bond index level and the individual bond level, indicating that volatility morphology factor is economically important and is key in allowing the extended model to explain credit spreads. Furthermore, this paper analyzes the asymmetric influences of monetary policy both on credit spreads and volatility morphology factor, and points out that the responses of credit spreads and asset volatility morphology to the impacts of monetary policy is consistent in the capital-strapped environments. To this end, monetary policy and liquidity, which are two factors that have been ignored by classic Merton model but proved to have significant influences on credit spreads, play a role in influencing credit spreads by changing the volatility morphology of asset value. Since volatility morphology can reflect the change of investors' expectation on the asset's default probability, the argument mentioned in the credit-spread puzzle that the fundamentals related to bond defaults cannot explain credit spreads needs to be reexamined.

Key words: Bond market, Credit spread puzzle, Merton model, Monetary policy, Volatility morphology

1 Xiao Hu, School of Finance, Southwestern University of Finance and Economics, Chengdu, 611130, China
Xinming Tian, Research Fellow of International Monetary Institute, Renmin University of China, Beijing; Department of Fixed Income, Rongtong Fund Management Co., Ltd., Beijing, 100032, China
Kuitai Wang, Research Fellow of International Monetary Institute, Renmin University of China, Beijing, 100872, China
E-mail addresses: huxiao@swufe.edu.cn (X. Hu), tianxm@rtfund.com (X. M. Tian), 1254442069@qq.com (K. T. Wang).

1. Introduction

Credit spread is the difference in yield between a risk-free bond and another bond of the same maturity but higher credit risk, such as a corporate bond. Having a thorough understanding of credit spreads is crucial to a financial practitioner. On the micro level, credit spreads embody the perceived default risk of a specific corporation. Whereas on the macro level, credit spread index reflects the systematic risk of the overall economy.

Numerous studies have analyzed and examined the determinants of credit spreads either theoretically or empirically. Most theoretical models fall into two categories. The first is structural model. This kind of model shows that on the brink of insolvency, the owner of an enterprise will choose to default. Therefore, probability of default is determined by the difference between bond price and equity value. Based on this idea, Merton (1974) builds Merton model under the assumption that the asset price series follows an Itô process and consequently expresses the value of a bond as the value of a corresponding risk-free bond minus that of a put option. He calculates the theoretical bond value and credit spread by means of the Black-Scholes Option Pricing Model (1973). Afterwards, many studies have made a series of modifications and revisions to classical Merton model.

Black and Cox (1976) relax the assumption that default would only occur on the maturity date of bonds and indicate that default would be triggered if the asset value fell below a certain threshold. Anderson and Sundaresan (1996) build a game model and come to a conclusion that even if asset value falls below the perceived trigger point, a bond issuer may not declare default immediately as timing is determined by a game process between shareholders and creditors, which will considerably increase the risk premium level. Mella-Barral and Perraudin (1997) follow this idea and obtain the analytical solution to bond prices. The work of Kim et al. (1993), Shimko et al. (1993) and Longstaff and Schwartz (1995) relax the assumption of a flat yield curve in Merton model, and assume that interest rates follow a mean-reverting CIR model or

Vasicek model. Since Merton model assumes that asset price is continuous, when the asset price is far from the default boundary, the default probability and credit spread are almost zero, which is inconsistent with market practice. To account for this, Zhou (2001) uses a Poisson process to describe the abrupt change of enterprise value and simulates the credit spreads via the Monte Carlo method.

The second kind of theoretical models is reduce-formed model. Contrary to structural models, reduce-formed models regard default probability as an exogenous variable and indicate that default probability depends on credit rating agencies or default acts like a completely random event. Therefore, default is solely determined by the stochastic process it follows and its corresponding intensity. Jarrow and Turnbull (1995) construct the process of default intensity and use bond market data to calculate the parameters of the process. The default probability in the model no longer depend on the financial data. This method serves as the cornerstone for constructing default intensity and has been adopted and modified by many subsequent studies. For instance, Lando (1998) changes the intensity from a constant to a random variable. The radiation model proposed by Duffie and Kan (1996) provides a method to calculate default probability under the stochastic intensity model. Some scholars combine the above two kinds of credit spread models and create the Hybrid Model. Duffie (2001) and Giesecke (2001) have made contributions to this field.

With the theoretical studies well under way, volumes of empirical studies have been conducted regarding to these models, among which literature examining structural models far outnumber that of reduce-formed models, as structural models have clear economic interpretations. One of the earliest empirical research in this field is that of Jones et al. (1984). It has empirically examined the difference between credit spreads derived from Merton model and that from the bond market data. Afterwards, the subsequent empirical studies generally follow the idea and have considered non-credit factors such as taxation, liquidity, and macroeconomic factors on credit spreads. Elton (2001) shows that credit spreads consist of risk premium, tax difference and expected default loss, among which risk premium carries the most weight, followed by tax difference, and expected default loss the last. Delianedis and Geske (2001) demonstrate that expected default loss only has an explanatory power of about 20% for credit spreads. They also point out the negative correlation between credit spreads and liquidity and the positive correlation between credit spreads and stock price volatility. Huang and Kong (2003) show that stock index, leading economic indicators, synchronous indices, and factors from Fama-French Model together could explain 40%-70% of the change in the credit spreads of corporate bonds. Furthermore, they perform tests on several classic structural models and conclude that the default expectation could explain no more than 20% of credit spreads.

Except for the above literature focusing on the U.S. bond market, a growing empirical studies explore credit spreads in other countries. These include the studies by Hattori et al. (2001), Batten et al. (2003) and Ohyama et al. (2007) on the Japanese bond market, the studies by Boss and Scheicher (2002), Van Landschoot and Astrid (2004) on the European bond market, and the studies by Wang et al. (2012), Fang et al. (2013) and Gao and Zou (2015) on China's bond market. In general, prior studies agree that fundamental factors related to default probabilities proposed by the traditional theoretical models have a very little explanatory power for credit spreads, while non-credit factors such as liquidity and monetary policy prove to perform much better. This creates a phenomenon described by Amato (2003) as the credit spread puzzle.

Some studies have provided explanations for the credit spread puzzle. For instance, Abramov et al. (2004) points out that investors' attitudes towards default risk vary with their preference of bonds with different credit quality. Accordingly, explanatory power of default risk in bonds with low credit grades is much higher than that of bonds with high credit ratings. Moreover, Amato (2005) proposes that the insufficient explanatory power of default risk on credit spread might be attributed to the negative skewness of the yield distribution and the difficulty in diversifying credit risks. Feldhütter and Schaefer (2018) indicate that the distribution of the historical default rate is skewed, meaning that the observed historical default rate is likely to be below the ex-ante default probability, so when testing a structural model that is calibrated to the historical default rate, predictions of the spread are likely to appear too low relative to the actual spread. According to Bai et al. (2020), the large market price of risk brought by securities that have significant exposure to downside tail risk imply that structural models of default are misspecified, and thus provide explanation for why these models significantly underestimate credit spreads. However, many of these explanations haven't derived from the credit risk model itself and offer little insights in the fundamental issue which underlies the conflicts, that is the incongruence between theories and empirical evidence related to credit spreads. More meaningful work should be conducted on the reasons behind the inefficiency of Merton model and increase its explanatory power by expanding and modifying the model.

In this paper, we first expand classic Merton model by using Asymmetric Exponential Power Distribution (AEPD) to introduce morphology factor of asset value volatility in the model. Serval numerical simulations help us show the effect of asset volatility morphology on credit spreads. We then find empirical supports to the extended Merton model by testing the explanatory power of the factors in the extended Merton model, especially the newly added volatility morphology factor, for credit spreads. By analyzing the expected default probability of investors implied in the volatility morphology factor, we further explore how monetary policy and liquidity, which are two non-credit factors excluded in classic Merton model, still associate with default risk when they influence credit spreads, and attempt to answer why fundamentals related to default risk have failed in explaining credit spreads.

2. The expanded Merton model

Classic Merton model and its various expanded structural models believe that risk-free rate, leverage ratio and asset price volatility are the main factors influencing the probability of default.

In terms of asset price volatility, classic Merton framework suggests that a higher volatility rate would widen credit spreads. But the real story is that volatility by itself does not necessarily increase the probability of default, and there is an asymmetric response of default probability to the positive and negative changes of asset price. Specifically, when the market value of a firm occurs positive fluctuation in consequence of good news, the probability of default would not increase. To acquire a better understanding of the mechanism by which asset price volatility influences credit spreads, we develop an expanded Merton model.

We argue that volatility factor includes not only volatility rate but also volatility morphology. Classic Merton model only covers volatility rate which has been shown by prior empirical studies to have little explanatory power for credit spreads. However, it doesn't mean that asset volatility morphology lacks explanatory power as well. As a matter of fact, volatility morphology provides far richer information than volatility itself. Let's take a simple numerical example, suppose that for one company, 9 out of 10 fluctuations in asset price are 1%, and only one is -9%, and for another company, asset price changes by -1% on 9 of these 10 fluctuations and by 9% on 1 fluctuation. Although both companies' volatility rates have a mean of zero and the same variance, the morphology of volatility is however drastically different. The volatility morphology factor is important in that changes in volatility morphology often stem from changes in monetary policy, liquidity conditions, and other fundamental factors. fluctuates by -1% on 9 of these 10 occasions and by 9% on 1 occasion. Although both have a mean of zero and the same variance, the pattern of volatility is however drastically different. The volatility pattern is important in that changes in volatility patterns often stem from changes in monetary policy, liquidity conditions, and other factors. Thus, the impact of these important factors on credit spreads might as well be incorporated in volatility morphology factor. In this paper, we expand classic Merton model based on that.

Merton (1974) believes that longing a corporate bond is equal to longing a risk-free bond while selling a put option on the issuer's assets. Let V be the enterprise value of a certain company at the beginning time t, and F be the face amount of all debt outstanding. Thus, the credit spread at time T is

$$CS\left(h,\sigma_v,(T-t)\right)=-\frac{1}{T-t}\log\left[N\left(d_2\right)+\frac{1}{h}N\left(-d_1\right)\right] \tag{1}$$

$$d_1=\frac{1}{2}\sigma_v\sqrt{T-t}-\frac{\ln(h)}{\sigma_v\sqrt{T-t}} \tag{2}$$

$$d_2=d_1-\sigma_v\sqrt{T-t} \tag{3}$$

where $h=Fe^{-r(T-t)}/V$ represents the leverage ratio when the risk-free rate is r. σ_v denotes the volatility rate.

We assume that enterprise value follows a random work with drift as follows:

$$\mathrm{d}V=(\alpha V-C)\mathrm{d}t+\sigma_v V\mathrm{d}z \tag{4}$$

where dz follows a standard Wiener process, z has a normal distribution, α denotes the return on assets and C represents interest income. Thus αV-C is the net cash inflow per unit of asset. In the case of a zero-coupon bond, C approaches zero and therefore

$$\mathrm{d}V=(\alpha V)\mathrm{d}t+\sigma_v V\mathrm{d}z \tag{5}$$

We modify the basic equation of enterprise value change by letting dz follows a random process comforting a AEPD distribution. A AEPD distribution is proposed by Zhu and Zinde Walsh (2009) and is short for asymmetric exponential power distribution. This distribution could better describe financial time series' data characteristics of heavy tails and negative skewness (Wu et al., 2016), and the asymmetry of distribution. A AEPD distribution has been applied in asset pricing. Wu (2016) constructs a stock price movement model using a AEPD distribution. Tian et al. (2015) apply this distribution to the pricing of European call options in the risk-neutral approach and empirically examine the implied option prices of convertible bonds. These studies show that a AEPD distribution effectively improve the fitting ability of asset pricing models to real financial time series data, and increase the forecasting level of models. As pricing of the underlying put is the essence of Merton framework, we would make some modifications to the function form of a AEPD distribution and then use it to optimize classical Merton model. A AEPD density function proposed by Zhu and Zinde-Walsh (2009) has the following form:

$$f_{\mathrm{AEP}}(y \mid \beta)\begin{cases} \left(\dfrac{\alpha}{\alpha^{*}}\right)\dfrac{1}{\sigma}K_{\mathrm{EP}}\left(p_1\right)\exp\left(-\dfrac{1}{p_1}\left|\dfrac{y-\mu}{2\alpha^{*}\sigma}\right|^{p_1}\right) & \text{if } y \le \mu \\ \left(\dfrac{1-\alpha}{1-\alpha^{*}}\right)\dfrac{1}{\sigma}K_{\mathrm{EP}}\left(p_2\right)\exp\left(-\dfrac{1}{p_2}\left|\dfrac{y-\mu}{2\left(1-\alpha^{*}\right)\sigma}\right|^{p_2}\right) & \text{if } y > \mu \end{cases} \tag{6}$$

where $\mu\in$R, σ>0, $\alpha\in(0, 1)$, p_1>0, p_2>0. μ and σ represent location and scale respectively. α is the skewness parameter, reflecting whether the tail is left- or right-skewed. p_1 and p_2 are two parameters reflecting the thickness of left and right tail respectively. α^* and $K_{EP}(p)$ are defined as

$$\alpha^{*}=\frac{\alpha K_{\mathrm{EP}}\left(p_1\right)}{\alpha K_{\mathrm{EP}}\left(p_1\right)+(1-\alpha)K_{\mathrm{EP}}\left(p_2\right)} \tag{7}$$

$$K_{\mathrm{EP}}(p)=\frac{1}{2p^{1/p}\Gamma(1+1/p)} \tag{8}$$

where Γ is the Gamma function and analytically $\Gamma(x)=\int_0^{\infty} y^{x-1}\mathrm{e}^{-y}\mathrm{d}y$.

Compared to a normal distribution, a AEPD distribution has more parameters to show the characteristics such as skewness, kurtosis and thick tail. The expectation and variance of a AEPD distribution are

$$E(x)=\frac{1}{B}\left[(1-\alpha)^2\frac{p_2\Gamma\left(\dfrac{2}{p_2}\right)}{\Gamma^2\left(\dfrac{1}{p_2}\right)}-\alpha^2\frac{p_1\Gamma\left(\dfrac{2}{p_1}\right)}{\Gamma^2\left(\dfrac{1}{p_1}\right)}\right] \tag{9}$$

$$Var(x)=\frac{1}{B^2}\left\{\left[(1-\alpha)^3\frac{p_2^2\Gamma\left(\frac{3}{p_2}\right)}{\Gamma^3\left(\frac{1}{p_2}\right)}+\alpha^3\frac{p_1^2\Gamma\left(\frac{3}{p_1}\right)}{\Gamma^2\left(\frac{1}{p_1}\right)}\right]-\left[(1-\alpha)^2\frac{p_2\Gamma\left(\frac{2}{p_2}\right)}{\Gamma^2\left(\frac{1}{p_2}\right)}-\alpha^2\frac{p_1\Gamma\left(\frac{2}{p_1}\right)}{\Gamma^2\left(\frac{1}{p_1}\right)}\right]^2\right\} \tag{10}$$

where B≡$\alpha K_{EP}(p_1)+(1-\alpha)K_{EP}(p_2)$.

We can further get the standardized form of a AEPD distribution. Suppose that random variable X has a standard AEPD distribution with parameter $\beta=(\alpha,\ p_1,\ p_2,\ \mu,\ \sigma)$. The standardized random variable z is

$$z=\frac{x-E(x)}{\sqrt{\mathrm{Var}(x)}}=\frac{x-w}{\sigma}\ f_{\mathrm{AEP}}(y\mid\beta)=\begin{cases}\delta\frac{\alpha}{\alpha^*}K_{\mathrm{EP}}(p_1)\exp\left(-\frac{1}{p_1}\left|\frac{w+z\delta}{2\alpha^*}\right|^{p_1}\right) & \text{if } z\le 0\\ \delta\left(\frac{1-\alpha}{1-\alpha^*}\right)K_{\mathrm{EP}}(p_2)\exp\left(-\frac{1}{p_2}\left|\frac{z}{2\left(1-\alpha^*\right)}\right|^{p_2}\right) & \text{if } z>0\end{cases} \tag{11}$$

When parameter $\beta=(\alpha=0.5,\ p_1=2,\ p_2=2, \mu=0, \sigma=1)$, z follows a standard normal distribution. Furthermore, Jacod and Shiryayev (1993) have shown that for any time $t>0$, there exists a corresponding noncontinuous independent increment process $Y(t)=\sum Y_t$. Y_i (i=1, 2, …, n) are random variables following an AEPD distribution. Subsequently, let $\phi(u)$ denotes the logarithm characteristic function of Y_i and there exists a corresponding martingale process:

$$Q(t)=\mathrm{e}^{tuY(t)-t\phi(u)} \tag{12}$$

Let $u=\sigma/i$ [2], the martingale would be $Q(t)=\mathrm{e}^{\sigma Y(t)-t\phi\left(\frac{\sigma}{i}\right)}$. Combining this with $V_t=V_0\mathrm{e}^{\mu t}$ (V_0 and V_t represent asset value at the beginning time and time t, μ represents discount rate), we can get the expression as follows:

$$V_t=V_0\mathrm{e}^{\mu t+\sigma Y(t)-t\phi\left(\frac{\sigma}{i}\right)} \tag{13}$$

[2] Here σ represents the standard deviation of annual returns, rather than the σ parameter in the AEPD model. As our AEPD distribution has been standardized, the σ parameter is always equal to 1. To simplify our illustration, we use the notation σ on both occasions.

Taking logarithms of both sides of equation (13), we get

$$\log(V_t) = \log(V_0) + \left(\alpha - \phi\left(\frac{\sigma}{i}\right)\right)t + \sigma Y(t) \tag{14}$$

where α is return. α in conjunction with p_1 and p_2 from equation (11) decide the shape of the standard AEPD distribution. In order to analyze the effects of the skewness and kurtosis of volatility morphology, we choose not to assign a value to α beforehand but assign the values to p_1 and p_2 and calculate the value of α based on equation (9). Skewness and kurtosis are the only two differences between a AEPD distribution and a normal distribution.

Let Y_i follows the standard AEPD distribution as shown in equation (11). When α=0.5, p_1=2, p_2=2, the AEPD distribution degenerates into a standard normal distribution (0, 1). The comparison between the AEPD distribution and the normal distribution is shown in Fig. 1 below.

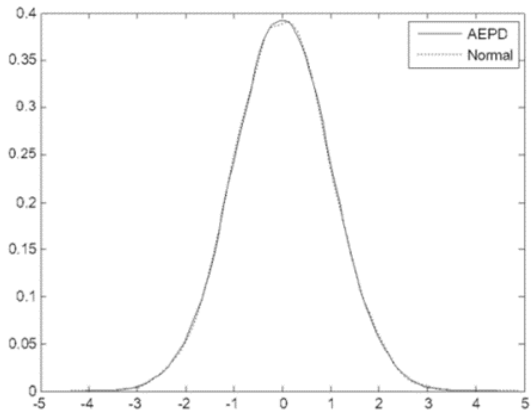

Fig. 1. The AEPD distribution and normal distribution when α=0.5, p_1=2, p_2=2

At this time, the logarithmic eigenfunction $\phi(\frac{\sigma}{i})$ equals to $\frac{1}{2}\sigma^2$. For asset price we have

$$\log(V_t) = \log(V_0) + \left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma W(t) \tag{15}$$

We could calculate the value of corporate debt using the risk neutral approach as follows:

$$F_t = \hat{E}\left[\min(V_T, B)\right] \tag{16}$$

In other words, if the company remains solvent, bond investors will receive the face value in full; otherwise they will get the market value of the issuer's assets. The yield and credit spread can be expressed as

$$\left(1-R_t\right)^{T-t}=F_t/B \tag{17}$$

$$CS_t=R_t-r \tag{18}$$

Based on our expended Merton model, equation (18) can be further discretized to

$$CS=CS\,(h,\sigma_V,(T-t),p_1,\ p_2,\alpha\,) \tag{19}$$

Compared to classical Merton framework, credit spreads under the Merton-AEPD model takes a more complicated form and there is usually no explicit solution for equation (19). Our study takes the numerical method to analyze the underlying relationship between the parameters of the Merton-AEPD model and credit spreads. Fig. 2 shows two typical morphologies (right-skewed and left-skewed) of the Merton-AEPD models under different parameters.

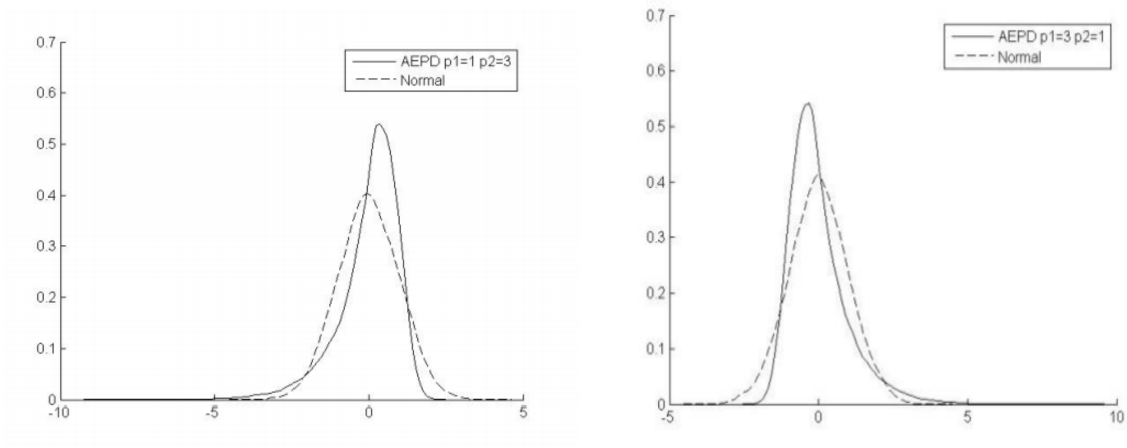

Fig. 2. The morphology of the AEPD distribution under different parameters.

As for a AEPD distribution, α is the most important parameter since it decides the skewed direction the distribution is. Besides, p_1 and p_2 also play a rule in that regard. As p_2 gets larger, the characteristics of the right kurtosis and heavy tail of the AEPD distribution are quite obvious, which will also cause the distribution to skew to right, and theoretically reduce the credit spread. The influence of p_1 on credit spreads is complex. On one hand, larger p_1 makes the distribution skew to left, increasing the credit spread. On other hand, when p_1 becomes larger, the distribution's right tail gets heavier and , making the distribution more positively skewed. There will be lower probability of extreme loss and corresponding credit spread. That is why we cannot come to a conclusion regarding the effect of p_1 on credit spreads.

To further examine whether α and p_2 significantly affect credit spreads, we set different assumptions about term to maturity *T*, leverage ratio *L*, risk-free rate *r*, and α, p_1, p_2 for volatility morphology and perform various numerical simulations. When regressing credit spread on α and p_2, both coefficients are negative and statistically significant. In other words, as the value of α or p_2 gets larger, the credit spread gets smaller. This is consistent with our argument that as negative skewness implies constant negative earnings, which is detrimental to investors' confidence and will impair the company's financing ability. Therefore, our Merton-AEPD model is effective in recognizing volatility morphology for which in the subsequent empirical researches we would use α and p_2 as agent variables.

3. Empirical analysis

We have pointed out in the previous section that volatility rate alone could not sufficiently describe the uncertainty regarding firm value, while volatility morphology provides far richer information. Based on the numerical simulations, credit spreads are negatively correlated with both α and p_2 under the Merton-AEPD model. Next, we conduct empirical studies on the effect of volatility morphology factor on credit spreads in China's bond market both at the bond index level and the individual bond level.

3.1. Empirical research at the bond index level

We first calculate the differences between ChinaBond Financial Corporate Bond Yield Curve (AAA/AA+/AA/AA-) and the yield of corresponding same-term government bonds [3]. We then take the arithmetic mean so as to obtain the monthly credit spreads series. Due to the differences

[3] Term to maturity include 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and 15 years.

in the starting point of the disclosures, length of the data series varies as shown in Table 1. As the credit spread series is non-stationary, we decide to take the natural logarithm of the original series and the new series have passed tests for stationarity. Besides, we estimate returns, standard deviations and volatility-pattern parameters from the CSI300 Index series based on classic Merton model and the Merton-AEPD model. As shown by Fig. 3 and Fig. 4, classical Merton model and our Merton-AEPD model provide nearly the same results of estimating yield and volatility rate.

Table 1.
Sample time spans for credit spreads under different credit rating levels.

AAA Rating	AA+ Rating	AA Rating	AA- Rating
2006.3-2019.12	2007.10-2019.12	2007.5-2019.12	2008.1-2019.12

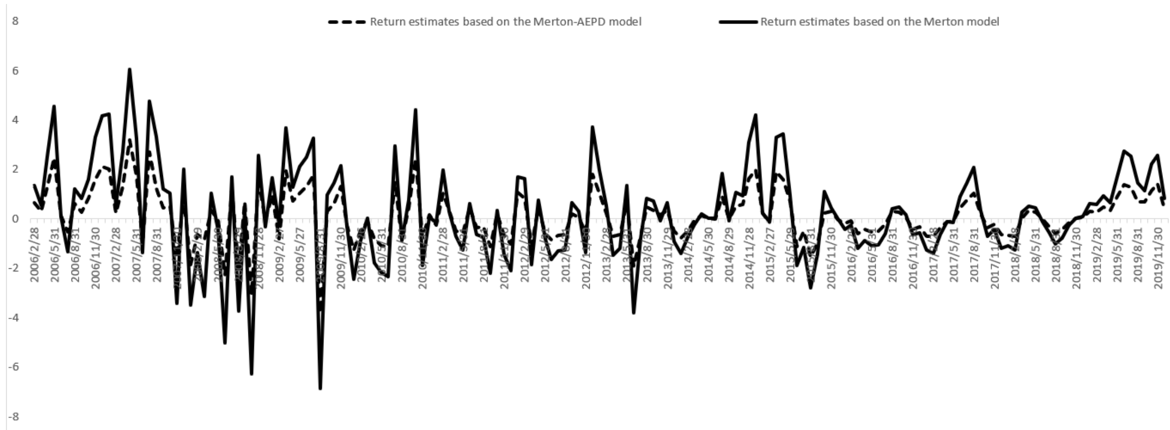

Fig. 3. Yield estimates based on classical Merton model and the Merton-AEPD model.

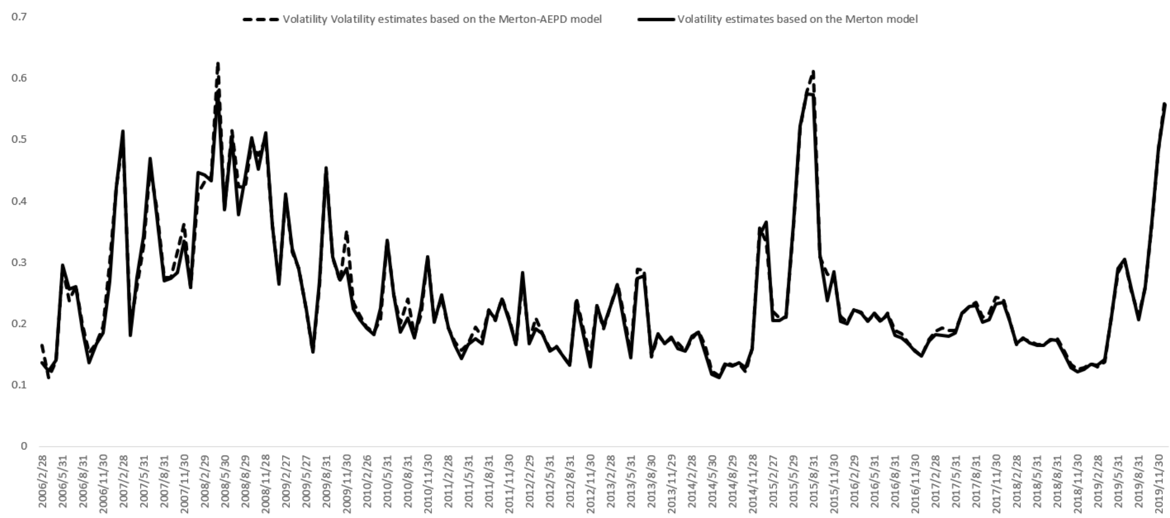

Fig 4. Volatility rate estimates based on classical Merton model and the Merton-AEPD model.

Subsequently, we apply the vector auto regression (VAR), to examine the effects of yield, volatility rate, and volatility morphology on credit spreads. To ensure the legitimacy of our regression, we have performed statistical tests on all the above data series and all of them are stationary. Table 2 exhibits results of the Granger causality tests for yield and credit spreads, while Fig. 5 reflects the impulse response of the corresponding credit spreads to yield. The results suggest that yield has a negative effect on credit spreads, which is consistent with classic Merton model. However, overall significance level of the test results is limited. For instance, the AA+ and AA- rated corporate bonds do not pass the Granger test. Table 3 presents results of Granger causality test for volatility rate and credit spreads, while Figure 6 shows the corresponding impulse response of credit spreads to volatility rate. The statistical tests suggest that volatility rate does not Granger cause credit spreads and the sign of the regression coefficient is inconsistent with that implied by classic Merton model. In other words, when volatility rate rises the credit spreads would fall. There are two possible explanations for this. First, favorable information regarding to the overall economy may make stock indexes more volatile, while narrow the credit spreads. Second, the CSI300 stock index could not be a substitute for bond yield indices. Overall, explanatory power of yield and volatility rate for credit spreads in classic Merton framework is limited.

Table 2.
Granger test for yield and credit spreads.

Null hypothesis	F-test
Yield does not Granger cause credit spread for AAA rated bonds	5.37**
Yield does not Granger cause credit spread for AA+ rated bonds	0.07
Yield does not Granger cause credit spread for AA rated bonds	2.93*
Yield does not Granger cause credit spread for AA- rated bonds	0.13

Note: ***, **, * indicate the significance level of 1%, 5%, and 10% respectively.

Table 3.
Granger test for volatility rate and credit spreads.

Null hypothesis	F-test
Volatility rate does not Granger cause credit spread for AAA rated bonds	0.73
Volatility rate does not Granger cause credit spread for AA+ rated bonds	0.51
Volatility rate does not Granger cause credit spread for AA rated bonds	1.04
Volatility rate does not Granger cause credit spread for AA- rated bonds	0.86

Note: ***, **, * indicate the significance level of 1%, 5%, and 10% respectively.

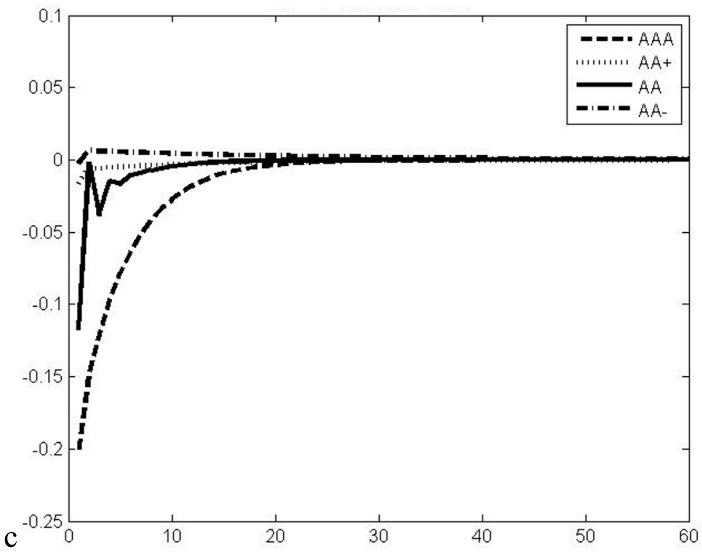

Fig. 5. Impulse response of credit spread to yield.

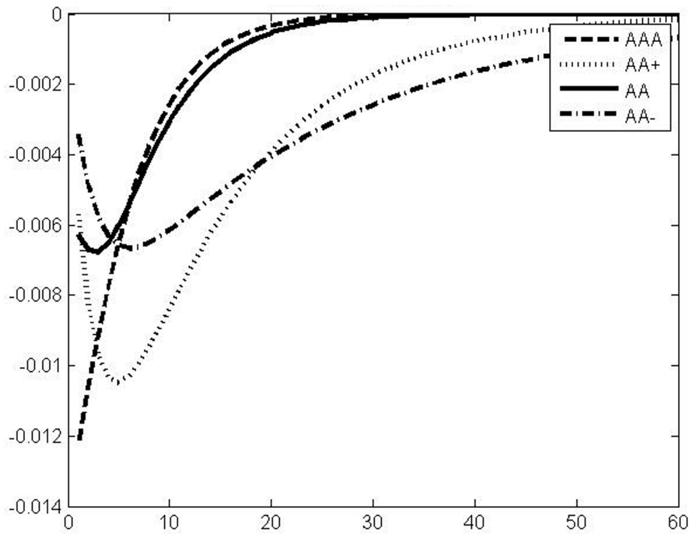

Fig. 6. Impulse response of credit spread to volatility rate.

Volatility morphology are described by α, p_1, p_2 from the AEPD distribution, among which α and p_2 are stably correlated with credit spreads in the theoretical model. The α series is stationary with a test statistic of -4.35 in the ADF test, which is significant at the 1% level. However, the p_2 series is non-stationary. We decide to use $-\alpha$ solely as a proxy for volatility morphology [4]. The results of VAR model are exhibited in Table 4 and Fig. 7. Table 4 indicates that volatility morphology Granger causes credit spreads. The Fig. 7 shows that credit spread affects volatility morphology

[4] In theory, as α enlarges, credit spreads decrease. In order to conveniently describe the results, we use –α instead of α in the VAR model to make sure volatility morphology and credit spread change in the same direction.

positively. That is if the volatility distribution gets more negatively skewed, the credit spreads widen. In conclusion, credit spread has a relatively stable positive response to the volatility morphology under the Merton-AEPD model. We can say that compared to yield and volatility rate, volatility morphology provides richer information on the changes in a company's value and have stronger predictive power for credit spreads.

Table 4.
Granger test for volatility morphology and credit spreads.

Null hypothesis	F-test
Volatility morphology does not Granger cause credit spread for AAA rated bonds	15.16***
Volatility morphology does not Granger cause credit spread for AA+ rated bonds	4.35***
Volatility morphology does not Granger cause credit spread for AA rated bonds	9.52***
Volatility morphology does not Granger cause credit spread for AA- rated bonds	2.72**

Note: ***, **, * indicate the significance level of 1%, 5%, and 10% respectively.

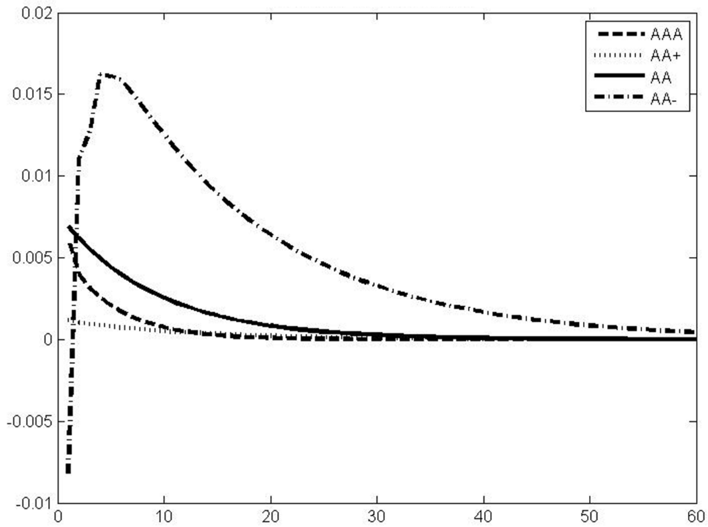

Fig. 7. Impulse response of credit spread to volatility morphology.

3.2. Empirical research at the individual bond level

To further verify the conclusion above, we also perform empirical analysis based on the more micro bond level data. Samples of individual bond have more variation. Besides, volatility morphology of a company's equity and its credit spread have one-to-one correlation. Our research only involves companies that issue both stocks and bonds at the same time. Moreover, many companies have serval bonds during the same period. In order to avoid the excessive influence of a single company on the overall sample, we only use the bond with largest issuance of a company as our research sample [5]. This leave us with 837 bonds issued before December 2019.

We use least square regression (OLS) to examine the impact of quarterly yield, volatility rate and volatility morphology on credit spread. The explained variable, credit spread, is calculated by taking the difference between the quarter-end ChinaBond yield of focal bond and the yield of the same-term treasury bond. As for the explanatory variables, yield and volatility rate are obtained from the quarterly stock trading data. The volatility morphology factors -α and p_2 is estimated under the Merton-AEPD model. Furthermore, based on existing literatures related to Merton model, we also control the quarterly slope of yield curve [6], leverage, firm fixed effect and quarter fixed effect in the regression model. As for the slope of the yield curve, we calculate the quarterly mean of spot yield and then use Nelson-Siegel (1987) model to obtain the yield curve slope. The model is

$$R(t,m)=\theta_1(t)+\theta_2(t)\frac{\tau}{m}\left[1-\exp\left(-\frac{\tau}{m}\right)\right]+\theta_3(t)\left\{\frac{\tau}{m}\left[1-\exp\left(-\frac{\tau}{m}\right)\right]-\exp\left(-\frac{\tau}{m}\right)\right\} \tag{20}$$

where $R(t, m)$ is the bond yield, m represents term to maturity, coefficient $\theta_1(t)$ is the asymptote of the long-term yield, and coefficient $\theta_2(t)$ measures how steep the yield curve is. Generally, $\theta_2(t)$ has a negative value, and as the absolute value of $\theta_2(t)$ gets larger, the spot curve gets steeper. coefficient $\theta_3(t)$ describes the curvature while τ describes the speed and degree that the long-term yield converges to its asymptote. As τ gets larger, the measure has more information about forward rate. In this case, we give τ a lower bond of 1 to focus more on the short-term rate.

By the time December 2019, there are 6,948 observations. The main reason for choosing quarterly data is that the volatility rate of individual stock is much larger than that of a stock index. We may not obtain robust estimators for the model parameters using monthly data or data of a higher frequency. Besides, the asset-liability ratio is also disclosed quarterly.

The empirical results are shown in Table 5. The regression coefficient of stock return is negative,

---

[5] If there were two bonds have the same face amount, we keep the one with longer term to maturity so as to have more data points.

[6] The form of term structure has rich economic meaning. Its steepness often represents investors' expectation of economic growth, inflation and so on (Hardouvelis, 1988; Minshkin, 1990).

but it is not significant. In fact, in the above empirical study at the bond index level, the effect of yield on credit spread is also relatively limited, and yield does not Granger cause credit spread for AA+ and AA- rated corporate bond. In addition, the regression coefficient of stock volatility is significantly negative, that is, when asset volatility rises, credit spread narrows, which is consistent with the empirical study at the bond index level and can't be explained by classical Merton model.

Table 5.
Regression Results for various factors on credit spreads.

	(1)	(2)
Stock return	-0.05	-0.02
	(0.07)	(0.06)
Stock volatility	-0.28***	-2.03***
	(0.09)	(0.10)
Volatility morphology: p_2	0.11***	
	(0.46)	
Volatility morphology: $\boldsymbol{\alpha}$	0.32**	
	(0.15)	
Slope of yield curve	-0.23**	-0.30**
	(0.19)	(0.18)
Leverage ratio	0.05***	0.05***
	(0.04)	(0.04)
Firm fixed effect	Yes	Yes
Quarter fixed effect	Yes	Yes
Constant	-0.19	-0.24
	(0.12)	(0.13)
Observation	6,948	6,948
R-square	0.53	0.54

Note: *t*-values are reported in parentheses under the estimation coefficient. ***, **, * indicate the significance level of 1%, 5%, and 10% respectively.

Regression coefficients for both α and p_2 are significantly positive, indicating volatility morphology has strong explanatory power for credit spread, which is consistent with the theoretical implications of the Merton-AEPD distribution. The expanded Merton model improve classical Merton framework by depicting the volatility factor more accurately.

4. The Influences of monetary policy and liquidity under the expanded Merton model

As summarized in the previous study on the existing research, the factors that affect credit spreads mainly include two categories. One is the fundamental factors related to the default probability defined by classic Merton model framework such as leverage ratio and asset volatility rate, which reflects investors' comprehensive judgment on the possibility of bond default; The other is monetary policy, liquidity and other factors. Although a large number of empirical studies have revealed that other factors such as monetary policy and liquidity have a significantly higher explanatory power for credit spreads than fundamental factors (Driessen, 2005; Wu and Zhang, 2008), but they often attribute the influences of monetary policy and liquidity to their own characteristics, and completely separate these factors from the possibility of default. This paper believes that factors such as monetary policy and liquidity do not directly affect credit spreads, and some of their effects still play a role by affecting the possibility of default. For example, under the tightening monetary policy, the reduction in the supply of funds in the bond market will directly affect the credit spreads of bonds. However, if investors observe the constraints of the tightening policy on the operation of the enterprise and increase the fear of corporate default, it is also related to the probability of default. In fact, the reason why this paper emphasizes the importance of asset volatility morphology is that volatility morphology often contains the information of "investors' expectation of default probability", which is affected by changes in monetary policy, liquidity and other no-credit factors.

Specifically, when the monetary environment is loose, companies tend to rely less on funds, and the marginal changes in monetary policy have less impact on business operations, and the impact is usually temporary. The return on asset may return to normal quickly, and investors' expectations for defaults caused by monetary policy and liquidity are small. In a tightening environment, monetary policy shock is more likely to be transmitted to a company's real operation activities. Therefore, the impact of monetary policy shock may be continuous, and investors' expectations of the probability of default increase. Here is a simple example to further illustrate the relationship between the continuity of monetary policy's influence and volatility morphology. For the sake of simplicity, the stock price is used to represent the enterprise value, assuming that the stock price return rate conforms to a normal distribution with a mean value of 0, and the total number of periods is 1300 periods. When the shock comes, if the impact is continuous, it is assumed that the stock price return rate will drop to the position of the average value of -2 and continue to fluctuate (still consistent with the normal distribution). Conversely, if the impact is short-term, it is assumed that the stock price return will only fluctuate 300 periods at the position where the mean is -2, and the remaining 1000 periods will still fluctuate at the position where the mean is 0. Fig. 8 shows the empirical distribution of returns under continuous and non-continuous impacts. Obviously, in the model with unsustainable impact, in addition to the decrease in the mean value, the empirical distribution of returns is obviously biased. It can be seen that volatility morphology that is neglected under the framework of classic Merton model will be shaped by changes in monetary policy and liquidity and partially mediate the influences of monetary policy and liquidity on credit spreads. If the idea is right, the argument of the credit spread puzzle that fundamental factors related to default cannot explain credit spreads will be weakened.

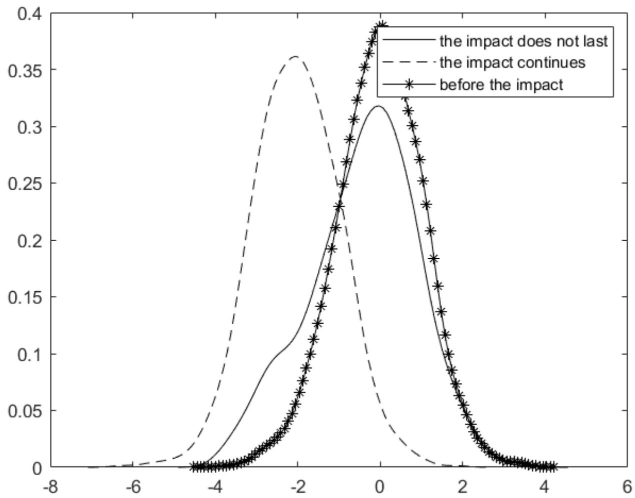

Fig. 8. Empirical distribution of returns under continuous and non-continuous impacts of monetary policy

We next analyze the influence of monetary policy on credit spreads and various factors in the expanded Merton model under different funding conditions, and then test the theoretical analysis above. If the asymmetry of monetary policy shock does exist and is consistent with the extended Merton model, it means that the mechanism by which monetary policy influence credit spreads is mediated by volatility morphology to some extent.

4.1. The impact of monetary policy on credit spreads

We first select the monthly average of the weighted interest rate of the seven-day repurchase in the interbank market from January 2002 to December 2019 as the proxy variable for monetary policy. The reasons are as follows. First, quantitative proxy variables such as loan growth and money supply have flaws in studying the bond market. Since both bonds and loans appear on the asset side of banks' balance sheet, the rapid growth of loans often means the shrinking of banks' allocation of bond assets, so the policy easing reflected by the loan growth rate sometimes represents the tightening of the bond market. At the same time, loan growth and money supply are to a certain extent the result of banks and residents' asset allocation and capital expenditure choices, which may lag behind investors' allocation of bonds. If using these variables as the proxy variables of monetary policy to study its impact on the bond market is quasi-inverted. In addition, these quantitative proxy variables are also endogenous and often deviate from real policy intentions. For example, although the growth rate of loans and M2 has declined in recent years, the monetary authorities have always been interested in guiding the decline in financing costs for policy purposes. Second, among the interest rate proxy variables, the inter-bank repo rate is the most representative. The inter-bank repurchase is the financial product with the largest transaction volume in substance and can most widely reflect the short-term cost of funds of financial institutions. Some scholars believe that the banks' cost of funds can be assumed to be the average of the seven-day repo rate and the one-year fixed deposit benchmark rate. Compared with other deposit and loan benchmark interest rates, the repo rate is daily data, so it also has sufficient variation, and because of its active trading, it can quickly reflect the tightness of funds. Third, judging from the practice of monetary authorities, China is paying more and more attention to open market operations and the management of short-term interest rate corridors. In recent years, various monetary tools such as Medium-term Lending Facility (MLF), Standing Lending Facility (SLF), and Short-term Liquidity Operations (SLO) introduced by the central bank are designed to strengthen the management of short-term interest rates. In fact, scholars generally agree that the monetary authority's control lies in short-term interest rates, and short-term interest rates should be used to guide changes of long-term interest rates. Of course, because this paper studies the bond market, the bond yield cannot be used as a proxy variable for monetary policy, and the seven-day repurchase that has high degree of marketization and logical causality with the bond market becomes the ideal choice.

We use the same monthly credit spread data in the above part of 3.1 to examine the impact of monetary policy on credit spreads based on the VAR model. The empirical results are shown in Table 6 and Fig. 7. It can be seen from Table 6 that monetary policy is the Granger reason for the credit spreads under each credit ratings. Fig. 7 shows that the impulse response of credit spreads to monetary policy shocks is positive.

Table 6.
Granger test for monetary policy and credit spreads.

Null hypothesis	F-test
Monetary policy does not Granger cause credit spread for AAA rated bonds	4.68**
Monetary policy does not Granger cause credit spread for AA+ rated bonds	4.23**
Monetary policy does not Granger cause credit spread for AA rated bonds	1.97***
Monetary policy does not Granger cause credit spread for AA- rated bonds	5.79**

Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively.

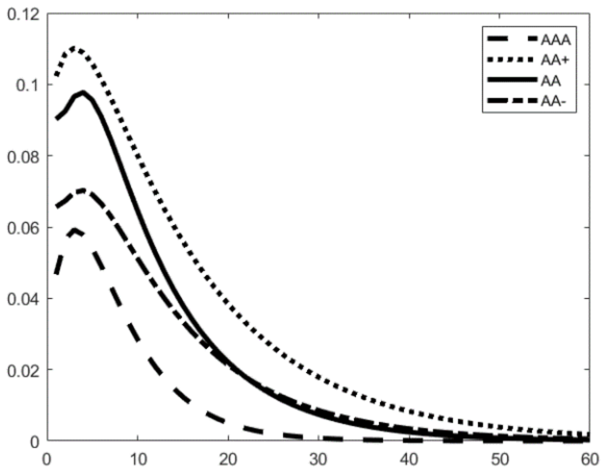

Fig. 9. The impulse response of credit spreads to monetary policy.

In order to test whether the impact of monetary policy has an asymmetric effect on credit spreads, this paper uses a smooth transition vector auto-regression (STVAR) for analysis. The lag order of the model is consistent with the previous VAR models, and the lag order of the transition variables is 1 order. First, we iterate the threshold value and smoothing coefficient of the four rated bonds separately to obtain four two-dimensional graphs of the likelihood function LR p-value (as shown in Figure 10-13), and then select the transition available for tests according to the two-dimensional graphs. It is not difficult to find that for the four groups of models, large areas of LR p-value less than 0.1 appear on both sides of the threshold from 3 to 4, so the range of available transition variable is relatively wide. In this paper, two cases of [loose (<2.5), tight (>4.5)] and [loose (<3), tight (>5)] are selected as control groups. The selection criterion of the smoothing coefficient is to make the LR p-value as small as possible under the existing parameters.

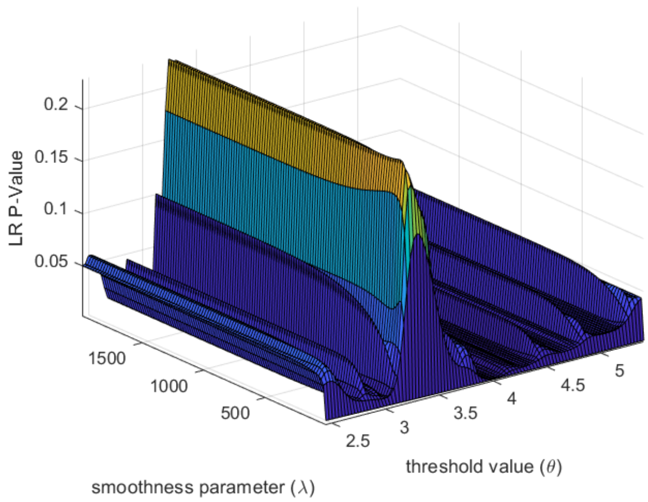

Fig. 10. Model parameter settings and LR p-value for AAA rated bonds.

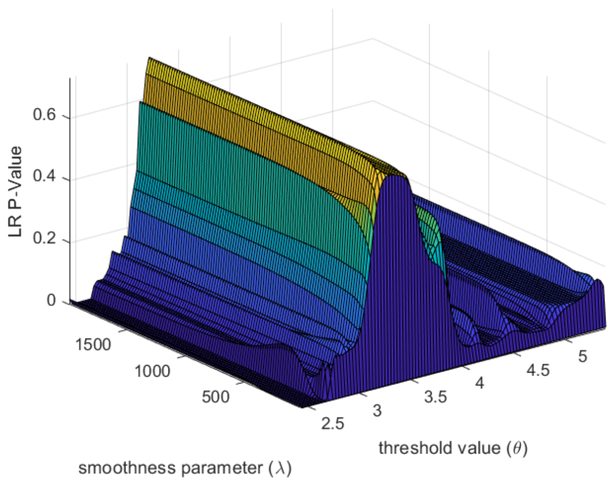

Fig. 11. Model parameter settings and LR p-value for AA+ rated bonds.

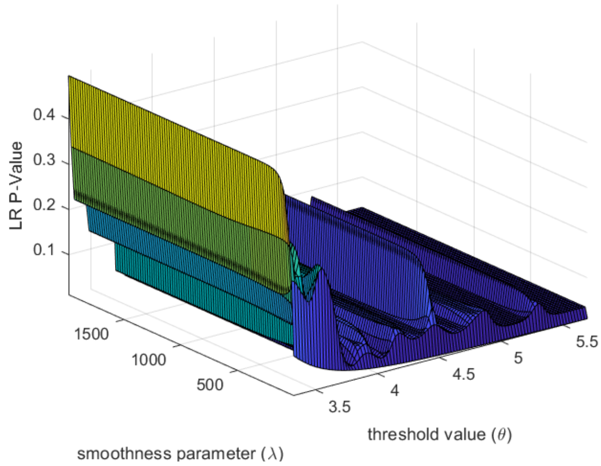

Fig. 12. Model parameter settings and LR p-value for AA rated bonds.

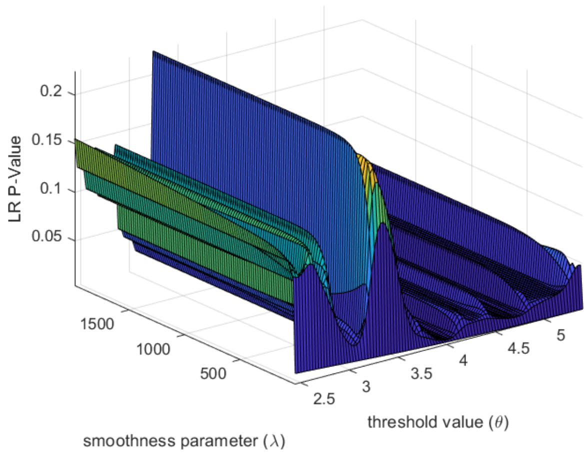

Fig. 13. Model parameter settings and LR p-value for AA- rated bonds.

Fig. 14 reflects the impulse response of credit spreads to the impact of monetary policy under the conditions of [loose (<2.5), tight (>4.5)]. And Fig. 15 reflects the impulse response of credit spreads to the impact of monetary policy under the conditions of [loose (<3), tight (>5)]. The results show that the impact of monetary policy has a significant asymmetric effect on credit spreads, that is, in a tight liquidity environment, credit spreads expand more, and in a loose liquidity environment, credit spreads expand less. This is basically consistent with the analysis of the theoretical part.

4.2. The impact of monetary policy on the factors of the expended Merton model

We further examine how monetary policy affects factors such as yield, volatility rate and volatility morphology that determine credit spreads in the Merton-AEPD model. STVAR models are performed using the seven-day repo rate and the yield, volatility rate and volatility morphology previously estimated based on the CSI300 index sequence. We iterate the threshold and smoothing coefficient for the yield, volatility rate and volatility morphology respectively to obtain three two-dimensional graphs of the likelihood function LR p-value. As can be seen from Figures 16-18, in the model about yield and seven-day repo rate, the threshold has a larger choice, while in the other two models, the area where the threshold can pass the non-linear test is relatively narrow. Considering the above situation comprehensively, the three models are compared in Table 7.

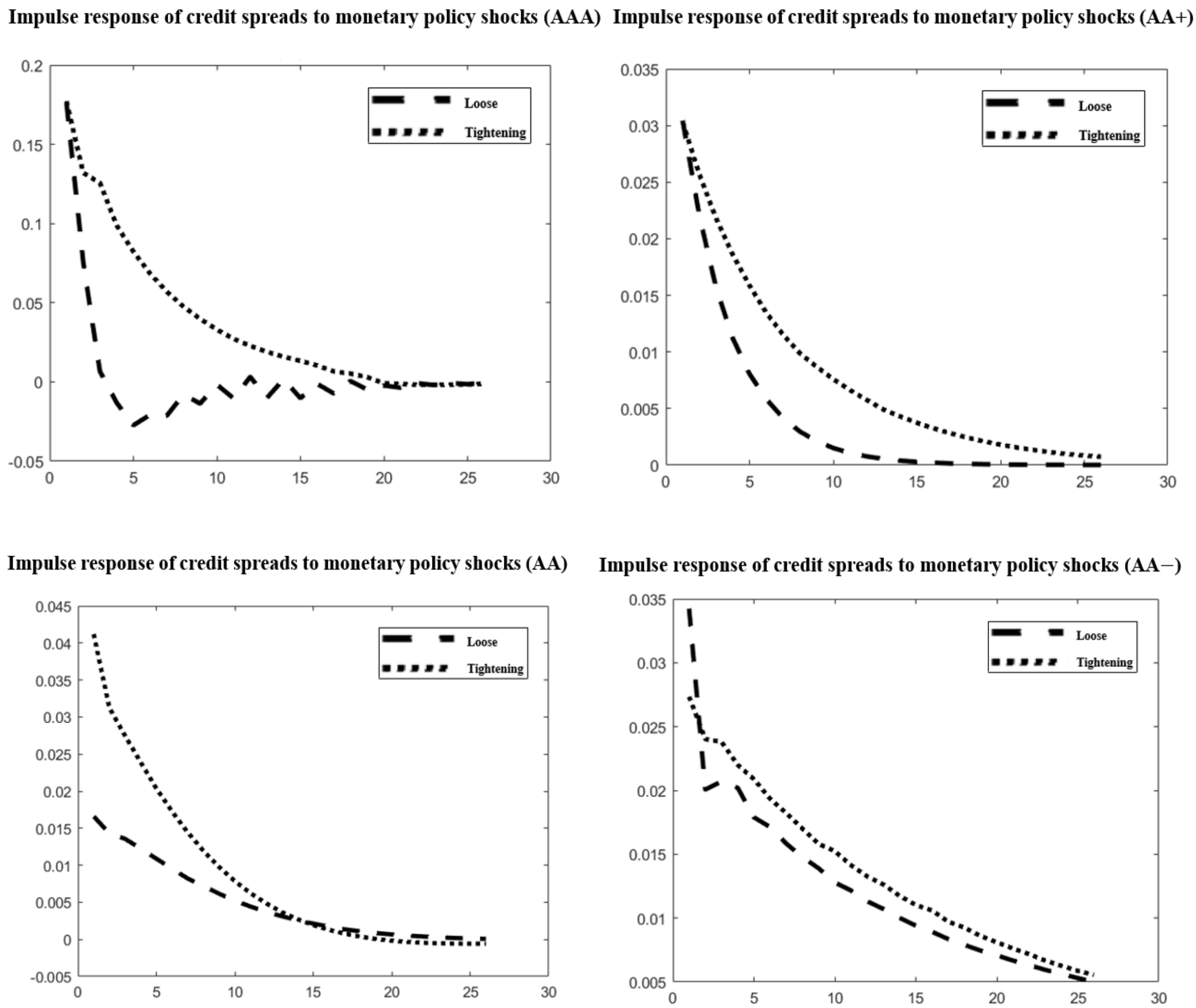

Fig. 14. Impulse response of credit spreads to monetary policy under the conditions of [loose (<3), tight (>5)].

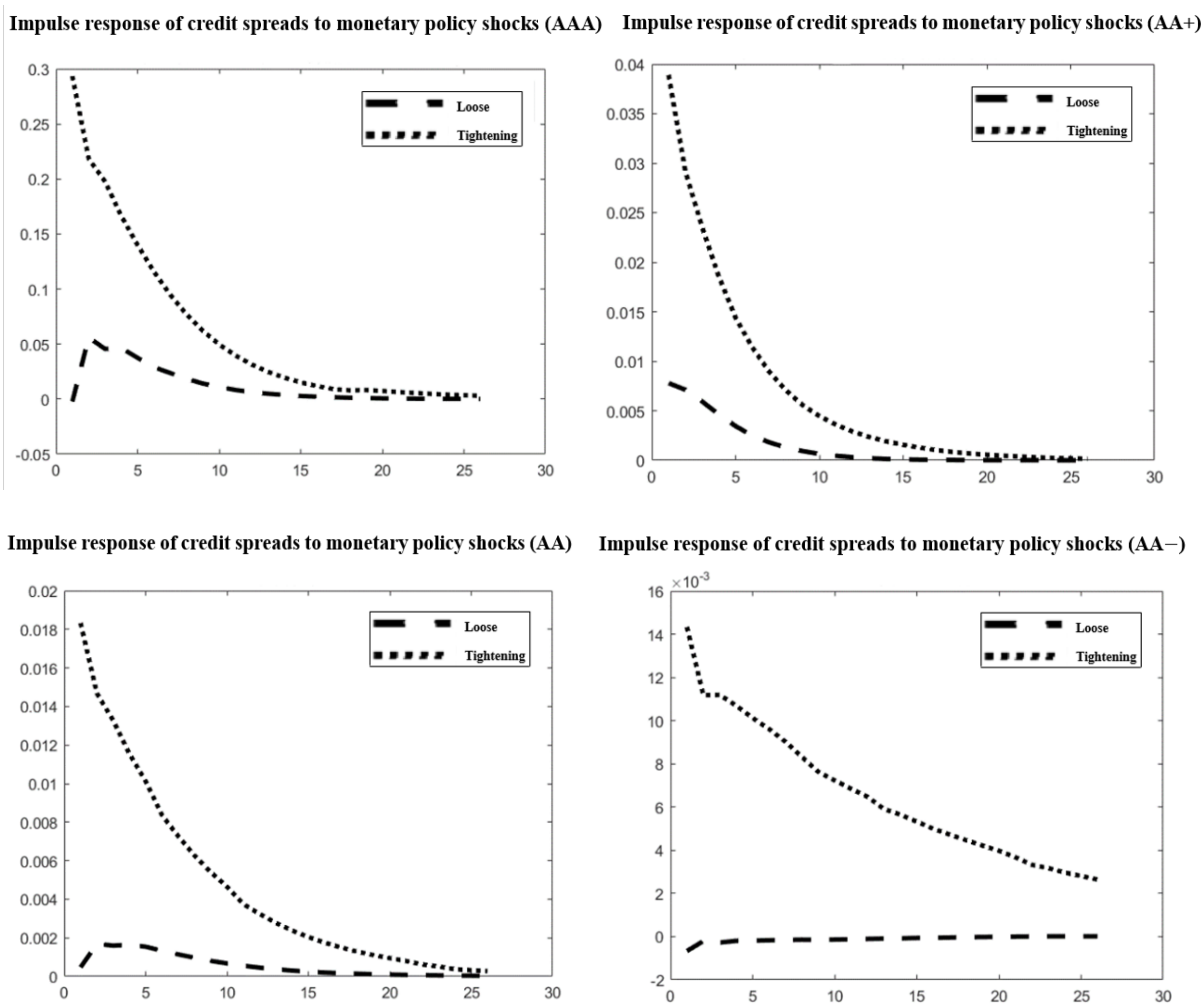

Fig. 15. Impulse response of credit spreads to monetary policy under the conditions of [loose (<3), tight (>4.5)].

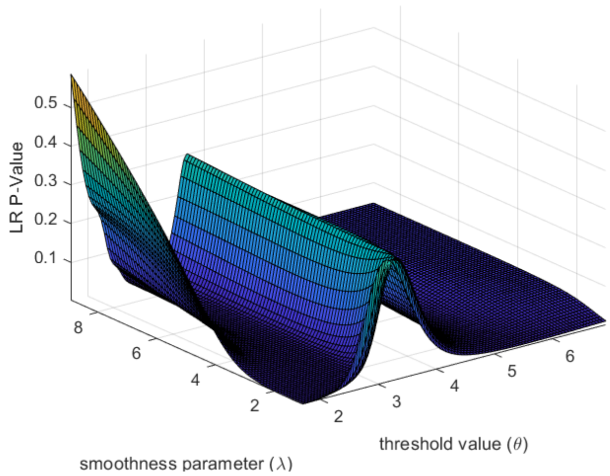

Fig. 16. Parameter setting and LR p-value for the yield model.

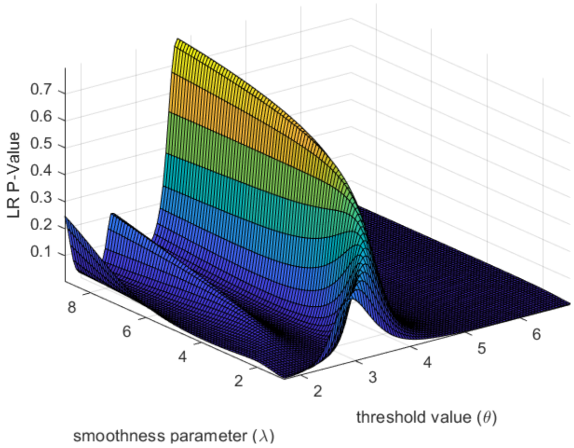

Fig. 17. Parameter setting and LR p-value for the volatility rate model.

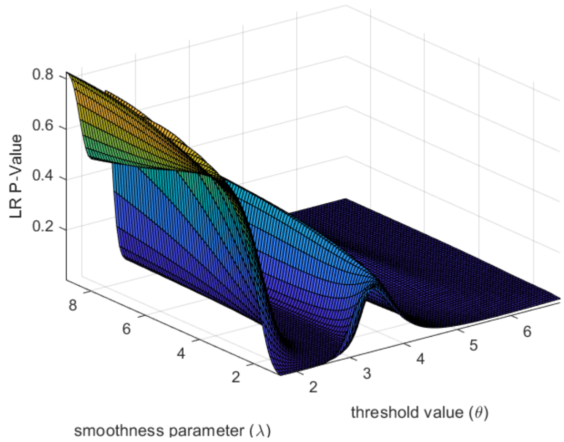

Fig. 18. Parameter setting and LR p-value for the volatility morphology model.

Table 7.
Model comparison.

Relationship	STVAR model settings	Whether there is asymmetry	Explanation
Yield and monetary policy	The transition variable lags by one period; the threshold value <3% >5%.	Asymmetry	In tight liquidity conditions, yields suffer a greater negative impact.
Volatility rate and monetary policy	The transition variable lags by one period; the threshold value <4% >5%.	No asymmetry	—
Volatility morphology and monetary policy	The transition variable lags by one period; the threshold value <4% >5%.	Asymmetry	In tight liquidity conditions, yields suffer a smaller negative impact.

Fig. 19 shows that yield shows asymmetry under the impact of monetary policy. When the liquidity is loose, the impact of monetary policy shock on yield is small, and when the liquidity is tight, the impact of monetary policy shock is greater. As can be seen from Fig. 21, the impact of monetary policy shock on volatility morphology also has obvious asymmetry, that is, monetary policy shifts volatility morphology to the right, but in a tight liquidity environment, the magnitude of the right skew will be smaller. The above empirical results are very consistent with the theoretical analysis corresponding to Fig. 8. When a monetary policy shock occurs, a decline in yield will definitely cause volatility morphology to be right-biased, and the continuity of the influence determines the magnitude of the right-bias. In a tight liquidity environment, volatility morphology has a smaller right skew, indicating that the impact of monetary policy is more sustainable.

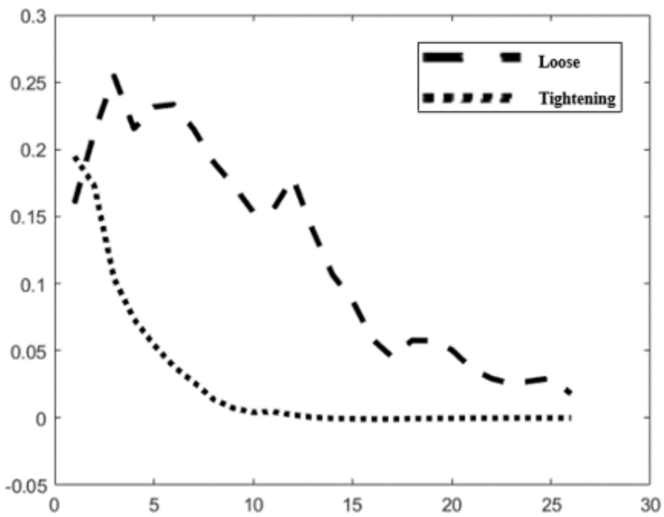

Fig. 19. Impulse response of yield to monetary policy.

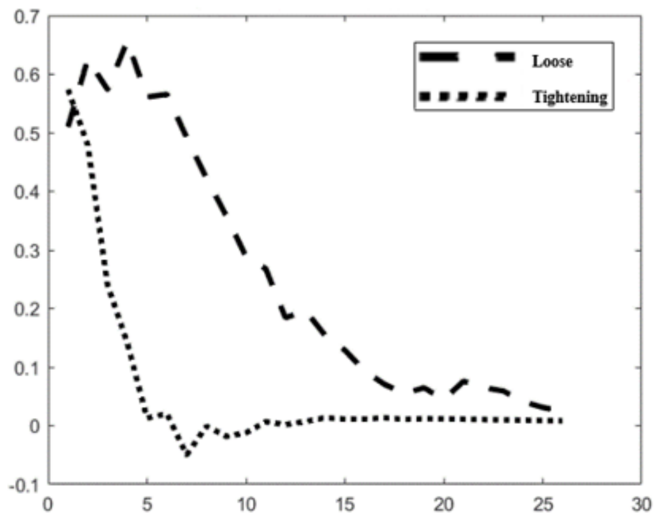

Fig. 20. Impulse response of volatility rate to monetary policy.

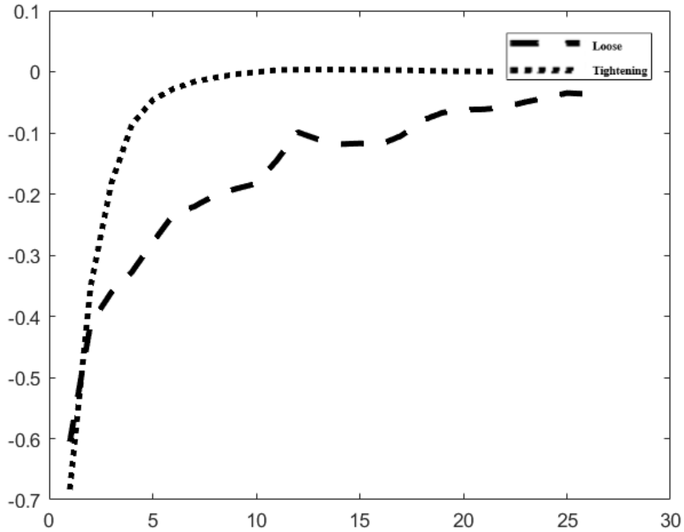

Fig. 21. Impulse response of volatility morphology to monetary policy.

Combining the research on the relationship between volatility morphology and credit spreads in the previous section and on the asymmetric impact of monetary policy shock on credit spreads, we indicate that volatility morphology plays an important mediating role in the transmission mechanism of the asymmetric effects of monetary policy on credit spreads. To further explain, the changes in credit spreads brought about by monetary policy and liquidity factors can be explained by the volatility morphology emphasized by our expanded Merton model. Since asset volatility morphology can reflect the changes in investors' expectation of default under the impacts of monetary policy and liquidity, the influences monetary policy and liquidity cannot be completely stripped from the default factors as the previous literature believes.

In addition, the empirical results in Fig. 21 also point out that under the impact of monetary policy, volatility rate tends to expand, but there is no significant asymmetry in a loose or tight liquidity environment. It should be noted that although the empirical study in the previous section found that rising volatility rate will reduce credit spreads, it cannot be asserted that monetary policy shock narrowed credit spreads by increasing volatility. This is because there are many reasons for the increase in volatility. The increase in volatility caused by the tight liquidity is often negative, and logically, credit spreads should not decrease.

5. Concluding remarks

This paper expands classic Merton model by introducing morphology factor of asset value volatility, and uses empirical studies to reveal the explanatory power of the extended mode. To some extent, the extended Merton model deals with the inconsistency between the structural approach to credit risk and the empirical evidences. Further studies show that no-credit factors such as monetary policy and liquidity, which have been ignored by classic Merton model but proved to hold significant explanatory power on credit spreads, play a role in influencing credit spreads by changing the volatility morphology of asset value, could be incorporated in asset volatility morphology. This paper concludes that it may be inappropriate to simply refer the phenomenon that the factors related to default probabilities proposed by the previous theoretical models fail to explain credit spreads as the credit spread puzzle.

We argue that there are two reasons why classical Merton model underestimate credit spreads. First, existing Merton framework ignores some fundamental factors. Especially when the neglected factors are driven by non-credit factors such as monetary policy and liquidity and reflect investors' fears of default, the model spreads become lower. The empirical results based on STVAR approach support this point. Second, the explanatory power of theoretical models will be limited if we only consider the issuers' real state of operation while regards other factors to be unrelated to default risks. In fact, as this paper demonstrates, changes in credit spreads resulting from shocks of monetary policy and liquidity may trace back to default risks. Non-credit factors may not be reflected in the operation state of companies directly, but they may be reflected in the expectations of investors. The change of asset volatility morphology under the monetary policy shock provides evidence to our arguments

By unraveling the credit spread puzzle, our paper also shed new lights on the understanding of China's bond market. In essence, credit spread is the capitalization of the default probability. Because the rigid payment phenomena exist at times, many financial practitioners and scholars believe that

China’s bond market is still immature and the credit spreads are more of a function of liquidity and investor psychology. Accordingly, the credit spread puzzle is often cited as evidence of the inefficiency and irrationality of China’s bond market. Based on the research context of China’s bond market, our paper provides estimates of default expectation risk premium implied in asset volatility morphology and document that it can be a key driver of credit spreads, which means that China’s bond market has a degree of pricing capability and allocation efficiency.

References

Amato, J. D., & Remolona E. M., (2003). The credit spread puzzle. *BIS Quarterly Review*, December, 51-63.

Amato, J. D. (2005). Risk aversion and risk premia in the CDS market. *BIS Quarterly Review*, December, 55-68.

Anderson, R. W., & Sundaresan, S. (1996). Design and valuation of debt contracts. *Review of Financial Studies*, 9(1), 37-68.

Avramov, D., Jostova G., & Philipov, A. (2007). Understanding changes in corporate credit spreads. *Financial Analysts Journal*, 63(2), 90-105.

Bai, J., Goldstein, R. S., & Yang, F. (2020). Is the credit spread puzzle a myth?. *Journal of Financial Economics*. 137(2), 297-319.

Batten, J. A., Hogan W. P., & Pynnönen, S. (2003). The time-varying behavior of credit spreads on Yen Eurobonds. In J. Jay Choi and T. Hiraki (ed.) T*he Japanese Finance: Corporate Finance and Capital Markets in Changing Japan*. Emerald Group Publishing Limited, 379-404.

Boss, M., & Scheicher, M. (2002). The determinants of credit spread changes in the Euro area. *Bank of International Settlements Papers*, (12), 181-199.

Black, F., & Cox, J. C. (1976). Valuing corporate securities: Some effects of bond indenture provisions. *Journal of Finance*, 31(2), 351-367.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3), 637-654.

Delianedis, G., & Geske, R. (2001). The components of corporate credit spreads: Default, recovery, tax, jumps, liquidity, and market factors. Working Paper, UCLA.

Driessen, J. (2004). Is default event risk priced in corporate bonds?. *Review of Financial Studies*, 18(1), 165-195.

Duffie, D., & Kan, R. (2010). A yield-factor model of interest rates. *Mathematical Finance*, 6(4), 379-406.

Duffie, D., & Lando, D. (2001). Term structures of credit spreads with incomplete accounting information. *Econometrica*, 69(3), 633-664.

Elton, E. J., Gruber, M. J., Agrawal, D., & Mann, C. (2001). Explaining the rate spread on corporate bonds. *Journal of Finance*, 56(1), 247-277.

Gao, Q., & Zou, H. F. (2015). A comparative study on pricing in the secondary market of corporate bonds and corporate bonds, *Journal of Financial Research*, (1), 84-100. In Chinese.

Giesecke, K. (2004). Correlated default with incomplete information. *Journal of Banking & Finance*, 28(7), 1521-1545.

Fang, H. X., Shi, J. K., & Zhang, G. B, (2013). The nature of property rights, information quality, and corporate bond pricing: Empirical evidence from China's capital market. *Journal of Financial Research*, (4), 170-182. In Chinese.

Feldhütter, P., & Schaefer, S. M. (2018). The myth of the credit spread puzzle. *Review of Financial Studies*, 31(8), 2897-2942.

Hardouvelis, G. A. (1988). The predictive power of the term structure during recent monetary regimes. *Journal of Finance*, 43(2), 339-356.

Hattori, M., Koyama, K., & Yonetani, T. (2001). Analysis of credit spread in Japan’s corporate bond market. The changing shape of fixed income markets: A collection of studies by Central Bank economists. *Bank of International Settlements Papers*, (5), 113-146.

Huang, J., & Kong, W. (2003). Explaining credit spread changes: New evidence from option-adjusted bond indexes.

Journal of Derivatives, (5), 30-44.
Jarrow, R. A., & Turnbull, S. M. (1995). Pricing derivatives on financial securities subject to credit risk. *Journal of Finance*, 50(1), 53-85.
Jones, E. P., Mason, S. P., & Rosenfeld, E. (1984). Contingent claims analysis of corporate capital structures: An empirical investigation. *Journal of Finance*, 39(3), 611-625.
Kim, J., Ramaswamy, K., & Sundaresan, S. (1993). Does default risk in coupons affect the valuation of corporate bonds?: A contingent claims model. *Financial Management*, 22(3), 117-131.
Lando, D. (1998). On Cox processes and credit risky securities. *Review of Derivatives Research*, 2(2-3), 99-120.
Longstaff, F. A., & Schwartz, E. S. (1995). A simple approach to valuing risky fixed and floating rate debt. *Journal of Finance*, 50(3), 789-819.
Mella–Barral, P., & Perraudin, W. (1997). Strategic debt service. *Journal of Finance*, 52(2), 531-556.
Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29(2), 449-470.
Mishkin, F. S. (1990). The information in the longer maturity term structure about future inflation. *Quarterly Journal of Economics*, 105(3), 815-828.
Nelson, C. R., & Siegel, A. F. (1987). Parsimonious modeling of yield curves. *Journal of Business*, 60(4), 473-489.
Ohyama, S., & Sugimoto, T. (2007). The determinants of credit spread changes in Japan. Working Paper, Bank of Japan.
Shimko, D. C., Tejima, N., & Van Deventer, D. R. (1993). The pricing of risky debt when interest rates are stochastic. *Journal of Fixed Income*, 3(2), 58-65.
Tian, X. M., Li L. L., & Zhen, S. Q., (2015). AEPD distribution and option pricing: Theoretical model and analysis of the "right value" of convertible bonds, *Review of Investment Studies*, (5), 108-117. In Chinese.
Van Landschoot, A. (2004). Determinants of Euro term structure of credit spreads. Working Paper, National Bank of Belgium and Ghent University.
Wang, A. X., Xie W. Z., & Yu, W. L. (2012). Empirical analysis of the composition and influencing factors of China's corporate bond spreads, *Journal of Management Science in China*, (5), 32-41. In Chinese.
Wu K. P., Tian X. M,, & Li, L. L. (2016). A stock price model based on AEPD distribution and its European option pricing. *Journal of Applied Statistics and Management*, (3), 560-570.
Wu, L., & Zhang, F. X. (2008). A no-arbitrage analysis of macroeconomic determinants of the credit spread term structure. *Management Science*, 54(6), 1160-1175.
Zhou, C. (2001). The term structure of credit spreads with jump risk. Journal of Banking & Finance, 25(11), 2015-2040.
Zhu, D., & Zinde-Walsh, V. (2009). Properties and estimation of asymmetric exponential power distribution. *Journal of Econometrics*, 48(1), 86-99.