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ARE THE CREDIT SPREADS IN CHINA AND THE U.S. AFFECTED BY THE SAME FACTORS? A POSSIBLE SOLUTION BASED ON GARCH FAMILY MODELS

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ABSTRACT

Based on the Generalized Auto-regressive Conditional Heteroskedasticity (GARCH) family models of normal distribution and Student's t-distribution, this paper fits the changes in credit spreads in China and the U.S. with various ratings and maturities, and compares their fitting effects. We found that Exponential GARCH (EGARCH) and Power GARCH (PGARCH) models with leverage effect are more suitable for modeling China and US credit spreads. Furthermore, Student's t-distribution can improve the model compared with normal distribution. In addition, based on the optimal GARCH model, this paper compares the factors influencing China and US credit spreads. The empirical results show that the change in credit spreads in China is affected by risk-free interest rate, stock market volatility and bond market liquidity. Besides, the credit spreads in China are more susceptible to the above factors than those in the U.S. Finally, this paper puts forward policy suggestions to develop China's bond market.

1. INTRODUCTION

With the rapid development of China's bond market and the deepening of its opening up to the world, the scale of China's bond market is gradually expanding and integrating into the global financial market. By January 2020, the escrow balance of China's bond market has reached 100.4 trillion CNY, which ranked as the second largest bond market in the world after the United States. However, China's bond market was established much later than that of the U.S. Therefore, it lacks product variety and requires strict regulation, resulting in many theoretical and practical differences between the bond markets of the two countries. Credit spreads are an important indicator profiling the characteristics of the bond market. This article attempts to compare the modeling effects of GARCH family models on credit spreads, and analyzes the factors affecting the corporate bond credit spreads in the two countries, so as to provide policy suggestions for China's bond market.

The credit spreads of corporate bonds have attracted the attention of numerous researchers. In the empirical research on the determinants of corporate bond credit spreads, Yang *et al.* (2020) conduct a study on the credit spreads of bank bonds and corporate bonds in China. They find that the spreads increased significantly after the "Interest Rate Reform" in 2014, which removed government's guarantees on certain corporate bonds. Kwon's (2020) research shows that there is a strong positive correlation between the financial uncertainty measured by VIX and the change of credit spreads. In recent years, some scholars try to explore the determinants of credit spreads by decomposing the spreads. Huang *et al.* (2012) conduct a systematic study on different structured models. They find that the credit risk cannot fully explain the change in credit spreads of corporate bonds. He believes that the credit spreads not only reflect its credit risk, but may also include other potential risks such as liquidity risk.

In the statistic studies of the spreads, empirical evidence shows that credit spread may have auto-correlation and non-normal distribution characteristics. Cai and Jiang (2008), Hibbert *et al.* (2011) and Clark (2018) show that the credit spread index of US corporate bonds have the features of time-varying volatility, skewness and thick tails. Through the studies of fixed income securities in the Euro area, Alizadeh and Gabrielsen (2013) also find that the change of credit spreads is likely to be skewed, fat-tailed, and change behavior over time. The above characteristics of credit spreads should be included in the credit spread models.

This paper applies a variety of macro factors, micro factors, and features of credit spreads mentioned in previous literature, such as time-varying volatility, skewness and thick tail. Considering the above factors, we fit the credit spreads with the GARCH family models and pick up the optimal fitting model with the regression results. Furthermore, based on the optimal fitting model, we compare the determinants of China and the United States credit spreads, and put forward policy suggestions for the stable development of China's bond market.

The marginal contribution of this article is that it provides an optimal GARCH model for credit spreads of China and the United States respectively. Furthermore, we discover that the China credit spreads are more susceptible to its risk-free interest rates, stock market volatility and liquidity factors.

The rest of the paper is organized as follows. Section 2 presents the methodology of this paper. In particular, we provide evidence to select the variables, and document the

GARCH family models as well. Section 3 presents and compares the results of the regression. Section 4 compares the differences in determinants of credit spreads between China and the U.S. Section 5 concludes our findings.

2. METHODOLOGY

2.1. The Variables

Referring to previous literature, we select the variables for credit spread modeling. In the structured model, risk-free interest rate is taken as the influencing factor of risky debt pricing. Osterholm (2018) and Karlsson *et al.* (2019) prove the negative correlation between interest rate and corporate bond credit spreads based on structured model. In addition, in the macroeconomic theory, the slope of yield curve is usually considered to contain the information of economic growth and economic outlook, where the inverted yield curve is usually associated with recession subsequently. Van (2008) suggests that there is a negative correlation between the slope and the change of credit spreads in bond market through empirical research. In addition, several studies on risk-free interest rate volatility provide evidence that interest rate volatility also has a significant impact on the change of credit spreads (Collin Dufresne *et al.*, 2001; Shinsuke and Takuya, 2007).

Under the hypothesis of continuous trading and efficient market, the structured model ignores the role of liquidity risk in the estimation of credit spreads. A branch of empirical researches based on structured models show that they systematically underestimate credit spreads. One of the most important reasons is that they do not consider the strong positive correlation between credit spreads and liquidity risk (Chen, 2015a, 2015b; Tsuruta, 2020; Gunay, 2020). Therefore, this article takes liquidity as one of the factors that affect the change in credit spread.

The stock price is an important indicator of the company’s financial and operating conditions. As a result, the stock market indexes were usually used to represent the situation of the whole equity market. Using Multifractal Detrended Fluctuation Analysis (MF-DFA) and Multifractal Detrended Cross-Correlation Analysis (MF-DXA), Shahzad (2017) finds that there is a strong correlation between bond market and equity market. Furthermore, Kwon (2020) shows that there is a significant positive correlation between index volatility and credit spreads.

Exchange rate risk refers to the unpredictable fluctuation of exchange rate and its impact on corporate operation. With the globalization of the financial market and the internationalization of business activities, more and more enterprises are facing exchange rate risk due to cross-border trades and overseas financing, affecting the bond yield of the company (Galai and Wiener, 2012). We add the factor of exchange rate into the model to reflect the impact of exchange rate risk on credit spreads.

In this context, the model can be specified asÿ

$$\Delta CS_t = C + \beta_1 \Delta r_t + \beta_2 \Delta \sigma_t^r + \beta_3 \Delta Slop_t + \beta_4 \Delta R_t^{stoxx} + \beta_5 \Delta \sigma_t^{stoxx} + \beta_6 \Delta Liq_t \\ + \beta_7 \Delta Exch_t + \varepsilon_t \tag{1}$$

where C is constant, Δ represents the change of variables, CS_t denotes the credit spread between corporate bond and treasury bond. The explicit information of variables is given in Table 1.

Table 1: The explicit information of variables

Classification	*Variable*	*Definition*	*Indicator*
Interest	r_t	risk-free interest rate	10-year treasury bond yield
	σ^r_t	volatility of risk-free interest rate	volatility of 10-year treasury bond yield
	$Slop_t$	slope of yield curve	the difference between the 10-year treasury bond yield and the 3-month treasury bond yield
Stock Market	R_t^{stoxx}	return of stock index	CN: return of CSI300 index
			US: return of S&P500 index
	s_t^{stoxx}	volatility of stock index	CN: volatility of CSI300 index
			US: volatility of S&P500 index
Liquidity Risk	Liq_t	liquidity of treasury bond market	treasury swap rate: 5-year
Exchange Rate Risk	$Exch_t$	exchange rate index	USD/CNY exchange rate index

2.2. GARCH Family Models

2.2.1. GARCH (p, q) model

Tang *et al.* (2018) find strong volatility clustering effect in China bond market. We adopt a series of conditional heteroscedasticity models to capture the ARCH effect and to describe the autocorrelation characteristics of daily credit spread changes. The GARCH (p, q) model expresses the variance at the current period as a linear function of itself of the past q periods and the square of the residual of past periods. The conditional variance of time t in GARCH(p, q) model is represented as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-j}^2 \tag{2}$$

where σ_t^2 represents the conditional variance of time t, α represents the estimator of ARCH effect, β represents the estimator of GARCH effect.

Specifically, the GARCH (1, 1) model can be expressed as

$$y_t = \gamma x_t + \varepsilon_t \tag{3}$$

$$\varepsilon_t = \sigma_t Z_t \tag{4}$$

$Z_t \sim i.\ i.\ d.\ N(0,1)$, and

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

2.2.2. Extension of GARCH Model

The GARCH (1,1) model cannot capture the leptokurtosis and fated-tail effect of credit spreads and the leverage effect of volatility. In addition, the model may violate the non-negative restriction of volatility because of its negative estimated coefficients. In addition, it cannot characterize correlation between the conditional variance and the conditional mean of the assets. As a result, the literature expands GARCH model from several aspects.

(1) Replace normal distribution with Student's t-distribution

Mcneil and Frey (2000) analyze the residual of GARCH model, and find that "statistical tests and exploratory data analysis confirm that the error terms or residuals do form, at least approximately, iid series that exhibit heavy tails" (p. 274). In order to capture the fated-tail and leptokurtosis effect in credit spreads, Student's t-distribution is used to replace the standard normal distribution in GARCH model. Let the degree of freedom equals to v, then we can get the following equation:

$$\varepsilon_t = (\sigma_t)^{\frac{1}{2}}\Pi_t, \qquad \Pi_t \sim Student(v) \tag{6}$$

(2) GARCH in mean (GARCH-M) model

Engle *et al.* (1987) propose GARCH-M model based on the ARCH model. Bonds are financial assets with expected returns closely related to expected risks. The GARCH-M model uses $f(\alpha_t^2)$, which is a function of σ_t^2, as an explanatory variable for credit spreads, so that the rate of return includes compensation for volatility. Linking the return of assets with the volatility of assets, the model better describes the relationship between returns and risks. In this article, the conditional variance σ_t^2 is used as representative of volatility factor of the GARCH-M model:

$$y_t = \gamma x_t + \lambda\sigma_t^2 + \varepsilon_t \tag{7}$$

$$\varepsilon_t = \sigma_t Z_t \tag{8}$$

where σ_t^2 in GARCH-M model (normal distribution) is the same as it in Equation (5).

(3) Exponential GARCH (EGARCH) model

The GARCH models above assume that the influence of negative and positive information was symmetrical. Nelson (1991) extends the GARCH model to the EGARCH model by loosing this assumption. The EGARCH model can better describe the asymmetry effect in financial market. In EGARCH model, the conditional variance σ_t^2 has the following form:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i Z_{t-i} + \sum_{i=1}^{q} \tau_i \mid Z_{t-i} \mid + \sum_{j=1}^{p} \beta_j \ \ln(\sigma_{t-i}^2) \tag{9}$$

The advantage of EGARCH model is that it adopts logarithmic form, so there is no restriction on the sign of parameter, and leverage effect can be enforced by the positive and negative of parameter τ. Parameter $\tau = 0$ indicates that there is no leverage effect. Therefore, the EGARCH model can better describe the asymmetry response of the conditional variance to the positive and negative impulses in the market.

(4) Power GARCH (PGARCH) model

Ding *et al.* (1993) propose the PGARCH model which relaxes the restriction that the power of the conditional variance in the GARCH model must be 2. The form of PGARCH (p, q, d) model is:

$$y_t = x_t\gamma + \varepsilon_t \tag{10}$$

$$\varepsilon_t = Z_t\sigma_t \tag{11}$$

$$\sigma_t^d = \alpha_0 + \sum_{i=1}^{q} \alpha_i (\mid \varepsilon_{t-i} \mid - \rho\varepsilon_{t-i})^d + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^d \tag{12}$$

where $\alpha_0 \geq 0, \alpha_i \geq 0, \beta_j \geq 0, d > 0$. Specifically, the PGARCH model is the same as GARCH (p, q) model when d = 2 and $\rho = 0$.

3. MODELLING SPREADS WITH GARCH FAMILY MODELS

3.1. Data and Summary Statistics

We collect China's corporate bond credit spread data from CIB Research. The sample covers data from January 1, 2010 to June 14, 2019 with various credit ratings and maturities. We use option adjusted spread (OAS) as the U.S. corporate bond credit spreads. The data of option adjusted spread is also from 2010 to 2019 with various credit ratings and maturities. Through the summary statistics of the corporate bond credit spreads, we find that the credit spreads in the two countries both have strong autocorrelation and heteroscedasticity, and show significant volatility clustering characteristic in all categories of rating and maturity. At the same time, through the Jarque-Bera test, the credit spreads of China and the United States both reject the assumption of normal distribution, and show positive skewness, leptokurtosis and fated-tail.

Table 2: Summary statistics of credit spread - China

	0.5-1Y	*1-3Y*	*3-5Y*	*5-10Y*	*10+Y*	*AAA*	*AA*	*AA-*
mean	106.51	93.39	91.88	61.09	60.41	76.37	195.29	143.05
median	106.07	92.99	89.13	55.74	58.79	72.83	185.22	125.61
max	208.08	181.06	188.35	151.54	127.98	175.09	353.28	290.75
min	40.92	47.32	52.84	15.69	13.22	36.46	96.05	79.99
std	29.40	22.51	20.24	24.23	20.44	19.51	58.80	49.49
skewness	0.30	0.41	1.79	0.79	0.57	1.63	0.88	1.47
Kurtosis	2.95	3.56	7.77	3.51	3.54	7.22	3.23	4.28
sample size	2357	2357	2357	2357	2283	2357	2357	2357
JB test								
Jarque-Bera	36.66	96.57	3501.68	270.86	151.80	2791.76	310.36	1009.51
P value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3: Summary statistics of credit spread – the U.S.

	1-3Y	*3-5Y*	*5-7Y*	*7-10Y*	*10-15Y*	*15+Y*	*AAA*	*AA*	*A*	*BBB*
mean	0.98	1.28	1.60	1.69	1.94	1.92	0.69	0.94	1.25	1.97
median	0.90	1.20	1.51	1.67	1.85	1.88	0.68	0.86	1.15	1.94
max	2.11	2.79	3.28	2.89	2.90	2.88	1.14	2.05	2.58	3.26
min	0.48	0.64	0.79	1.00	1.35	1.32	0.48	0.51	0.71	1.15
std	0.36	0.44	0.48	0.37	0.32	0.29	0.11	0.29	0.38	0.44
skewness	0.99	1.12	0.98	0.74	0.79	0.67	0.85	1.39	1.19	0.56
Kurtosis	3.30	4.00	3.65	3.26	3.03	2.99	4.17	5.06	4.04	2.79
sample size	2436	2436	2436	2436	2436	2436	2436	2436	2436	2436
JB test										
Jarque-Bera	410.94	606.16	432.59	230.63	255.06	180.41	432.62	1218.84	679.79	133.83
P value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Due to the non-normal characteristic of credit spreads, the traditional GARCH (1, 1) model may not be able to accurately capture the leverage effect, volatility persistence, leptokurtosis, fated-tail and positive skewness of credit spreads. In order to compare the ability to capture the above characteristics of GARCH family models (the GARCH (1,1) modelÿGARCH-M model, EGARCH model and PGARCH model), four models based on the standard normal distribution and the Student's t-distribution are used to fit the credit spreads in China and the United States with various maturities and ratings.

3.2. Model Estimation

This sector shows the regression results of the credit spreads under different GARCH models. The estimates of the GARCH (1,1) model (normal distribution) and the GARCH(1,1) model (Student's t-distribution) of credit spreads in China are shown in Table 4 and Table 5. The same estimates of credit spreads in the U.S. are shown in Table 6 and Table 7. The regression results of the other GARCH family models (normal distribution and Student's t-distribution) are shown in External Appendix A to D.

Table 4: GARCH (1,1) model (normal distribution) of China credit spreads

	AAA	*AA*	*AA-*	*<1Y*	*1-3Y*	*3-5Y*	*5-10Y*	*>10Y*
C	0.05	0.05	0.10	0.18*	0.03	-0.02	-0.01	-0.03
	(1.04)	(0.79)	(1.53)	(1.88)	(0.39)	(-0.38)	(-0.26)	(-0.54)
Δr_t	7.38***	2.42	5.97**	1.82	8.05**	6.54***	2.84	2.63
	(3.52)	(0.85)	(2.31)	(0.52)	(2.36)	(2.68)	(1.12)	(0.99)
$\Delta\sigma^r_t$	-2.14	9.84	28.77	-60.81	-25.44	19.17	-49.46***	2.85
	(-0.11)	(0.40)	(1.07)	(-1.28)	(-1.26)	(0.59)	(-3.06)	(0.14)
$\Delta Slop_t$	-1.21***	0.28	-0.01	2.22	-0.75	-1.71*	-3.08***	-0.61
	(-2.46)	(0.23)	(-0.01)	(1.27)	(-1.17)	(-1.74)	(-3.13)	(-0.55)
ΔR_t^{stoxx}	0.00	0.00	0.00	0.00**	0.00	0.00	0.00	0.00
	(1.42)	(0.59)	(0.85)	(2.08)	(0.33)	(-0.80)	(-1.37)	(-1.25)
$\Delta\sigma_t^{stoxx}$	0.15	4.87	-0.99	18.66**	-4.29	-6.86	-13.61**	-12.54**
	(0.03)	(0.78)	(-0.17)	(2.09)	(-0.67)	(-1.02)	(-2.38)	(-2.11)
ΔLiq_t	1.29	-1.31	-1.42	3.25**	-0.31	0.36	-0.46	0.76
	(1.26)	(-1.04)	(-1.08)	(1.99)	(-0.23)	(0.26)	(-0.34)	(0.59)
$\Delta Exch_t$	-0.03	0.12	0.07	-0.10	0.04	-0.08	0.05	0.12
	(-0.27)	(0.82)	(0.40)	(-0.55)	(0.28)	(-0.50)	(0.29)	(0.82)
Residual function								
ω	0.19***	0.24***	0.39***	0.78***	0.35***	0.13***	0.07***	0.07***
	(4.43)	(3.38)	(3.92)	(4.50)	(4.35)	(3.49)	(3.49)	(3.87)
ARCH($\propto$)	0.17***	0.14***	0.14***	0.16***	0.13***	0.08***	0.09***	0.08***
	(7.88)	(7.36)	(7.20)	(7.19)	(7.33)	(6.41)	(8.17)	(7.56)
GARCH(β)	0.80***	0.84***	0.81***	0.79***	0.82***	0.90***	0.90***	0.91***
	(34.53)	(40.41)	(30.35)	(29.24)	(37.12)	(59.45)	(85.08)	(86.00)
Goodness of fit								
Log-Likelihood	-2499	-2787	-2712	-3126	-2696	-2687	-2542	-2653
AIC	4.26	4.76	4.63	5.34	4.61	4.59	4.34	4.50
DW	1.71	1.60	1.62	1.77	1.83	1.76	1.91	1.91

Table 5: GARCH (1,1) model (Student's t-distribution) of China credit spreads

	AAA	AA	AA-	<1Y	1-3Y	3-5Y	5-10Y	>10Y
C	0.05	0.05	0.10	0.13	0.02	0.02	-0.02	-0.02
	(1.10)	(0.73)	(1.59)	(1.59)	(0.35)	(0.32)	(-0.32)	(-0.34)
Δr_t	4.01*	-0.37	3.08	2.34	3.86	5.36**	5.00*	2.83
	(1.85)	(-0.12)	(1.15)	(0.62)	(1.34)	(2.02)	(2.00)	(1.12)
$\Delta \sigma_t^r$	-5.68	-11.17	6.99	-28.26	-36.79*	43.96	0.46	10.59
	(-0.31)	(-0.40)	(0.25)	(-0.50)	(-1.72)	(1.40)	(0.02)	(0.45)
$\Delta Slop_t$	-0.78	0.59	0.13	1.54	-0.42	-0.78	-2.76***	-0.67
	(-1.14)	(0.44)	(0.11)	(0.87)	(-0.50)	(-0.80)	(-3.10)	(-0.61)
ΔR_t^{stoxx}	0.00	0.00	0.00	0.00*	0.00	0.00	0.00	0.00
	(0.91)	(0.21)	(0.60)	(1.80)	(0.08)	(-1.14)	(-0.47)	(-0.35)
$\Delta \sigma_t^{stoxx}$	-2.44	5.08	-0.19	7.50	-1.74	-9.32*	-11.39**	-11.65**
	(-0.51)	(0.79)	(-0.03)	(0.87)	(-0.26)	(-1.47)	(-2.23)	(-2.28)
ΔLiq_t	1.79*	-0.15	-0.12	1.89	0.36	1.22	-0.73	1.22
	(1.66)	(-0.11)	(-0.09)	(0.99)	(0.26)	(0.93)	(-0.61)	(0.97)
$\Delta Exch_t$	-0.09	0.18	0.13	-0.07	0.01	-0.11	0.06	0.34**
	(-0.79)	(1.15)	(0.85)	(-0.37)	(0.09)	(-0.78)	(0.38)	(2.47)
Residual function								
ω	0.20***	0.30**	0.52***	0.57***	0.33***	0.15**	0.05*	0.05**
	(3.16)	(2.74)	(3.02)	(2.83)	(3.01)	(2.41)	(1.87)	(2.02)
$ARCH(\alpha)$	0.17***	0.13***	0.15***	0.14***	0.13***	-0.09***	0.09***	0.08***
	(5.14)	(4.96)	(4.60)	(4.76)	(4.87)	(4.21)	(4.85)	(4.69)
$GARCH(\beta)$	0.80***	0.84***	0.78***	0.83***	0.82***	0.89***	0.91***	0.92***
	(23.85)	(28.87)	(17.81)	(26.23)	(25.32)	(37.54)	(54.35)	(64.70)
$Student(v)$	6.01***	6.10***	6.04***	4.88***	7.17***	5.54***	5.55***	4.66***
	(4.62)	(4.66)	(5.29)	(5.66)	(4.39)	(6.11)	(6.32)	(6.18)
Goodness of fit								
Log-Likelihood	-2378	-2762	-2680	-3091	-2679	-2649	-2503	-2593
AIC	4.07	4.72	4.58	5.28	4.58	4.53	4.28	4.43
DW	1.73	1.61	1.62	1.77	1.84	1.75	1.88	1.90

Table 6: GARCH (1,1) model (normal distribution) of the U.S. credit spreads

	AAA	*AA*	*A*	*BBB*	*1-3Y*	*3-5Y*	*5-7Y*	*7-10Y*	*10-15Y*	*>15Y*
C	-0.00***	-0.00**	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00	-0.00***
	(-0.93)	(-2.24)	(-3.73)	(-4.00)	(-3.47)	(-3.07)	(-3.88)	(-3.75)	(-0.66)	(-3.68)
Δr_t	-0.01	0.04***	0.01	0.02	0.01	0.01	0.02	0.00	0.02	0.01
	(-0.34)	(2.86)	(0.96)	(1.11)	(0.64)	(0.30)	(0.85)	(0.24)	(0.81)	(0.43)
$\Delta \sigma^r_t$	-0.04**	-0.01	-0.03**	0.02	0.00	-0.01	-0.01	0.02	0.00	-0.01
	(-2.41)	(-0.89)	(-2.08)	(1.19)	(-0.08)	(-0.48)	(-0.63)	(1.03)	(0.22)	(-0.33)
$\Delta Slop_t$	0.02	-0.03***	-0.01	-0.02	-0.01	-0.01	-0.01	-0.02	-0.01	-0.01
	(1.18)	(-2.78)	(-0.76)	(-1.21)	(-0.44)	(-0.43)	(0.59)	(-0.84)	(-0.27)	(-0.33)
ΔR_t^{stoxx}	0.00*	0.00	0.00	0.00**	0.00	0.00	0.00	0.00	0.00	0.00*
	(1.84)	(0.94)	(0.94)	(2.27)	(0.20)	(1.51)	(1.61)	(1.52)	(1.15)	(1.74)
$\Delta \sigma_t^{stoxx}$	-0.01	0.01	0.01	0.04	-0.03	0.01	0.05	0.03	0.07	0.05
	(-0.43)	(0.24)	(0.43)	(1.10)	(-0.90)	(0.19)	(1.54)	(0.60)	(1.51)	(1.61)
ΔLiq_t	0.01**	0.01	0.00	-0.01	0.02***	0.00	0.01	0.00	0.00	0.00
	(2.34)	(1.22)	(1.15)	(-1.33)	(3.22)	(0.89)	(0.83)	(0.58)	(0.05)	(0.06)
$\Delta Exch_t$	0.00**	0.00***	0.00***	0.00	0.02***	0.00***	0.00***	0.00	0.00**	0.00**
	(-2.23)	(-4.12)	(-3.17)	(-1.24)	(-3.11)	(-2.77)	(-3.44)	(-1.23)	(-2.10)	(-2.26)

Residual function										
ω	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(19.80)	(5.81)	(6.96)	(8.42)	(6.57)	(6.46)	(7.27)	(7.77)	(5.44)	(10.12)
ARCH(α)	0.16***	0.10***	0.16***	0.14***	0.14***	0.14***	0.19***	0.17***	0.04***	0.18***
	(14.64)	(21.76)	(19.41)	(18.18)	(15.70)	(17.20)	(19.84)	(14.41)	(17.07)	(18.21)
GARCH(β)	0.84***	0.90***	0.84***	0.84***	0.85***	0.84***	0.80***	0.82***	0.95***	0.80***
	(13.85)	(288.73)	(133.66)	(128.62)	(110.65)	(82.60)	(98.10)	(69.82)	(316.63)	(117.19)
Goodness of fit										
Log-Likelihood	6326	6548	6472	5857	6243	6184	5875	5788	5691	6129
AIC	-5.95	-6.16	-6.09	-5.47	-5.87	-5.82	-5.53	-5.44	-5.35	-5.77
DW	1.99	1.60	1.38	1.31	1.58	1.34	1.32	1.41	1.69	1.34

Table 7 GARCH (1,1) model (Student's t-distribution) of the U.S. credit spreads

	AAA	*AA*	*A*	*BBB*	*1-3Y*	*3-5Y*	*5-7Y*	*7-10Y*	*10-15Y*	*>15Y*
C	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(-0.54)	(-3.04)	(-3.78)	(-5.67)	(-4.84)	(-4.19)	(-5.12)	(-4.18)	(-3.48)	(-4.11)
Δr_t	0.00***	0.02**	0.01	0.02	-0.01	0.01	0.02	0.02	0.02	0.02
	(-0.32)	(1.86)	(0.58)	(1.14)	(-0.37)	(0.82)	(1.21)	(0.99)	(1.20)	(1.10)
$\Delta\sigma^r_t$	0.00	0.01	0.00	0.02	0.01	0.01	0.00	0.00	-0.01	0.00
	(-0.36)	(0.48)	(-0.23)	(0.96)	(0.79)	(0.82)	(0.25)	(-0.04)	(-0.38)	(0.26)
$\Delta Slop_t$	0.01	-0.02*	-0.01	-0.01	0.00	-0.01	-0.02	-0.02	-0.01	-0.02
	(0.71)	(-1.65)	(-0.63)	(-0.86)	(0.18)	(-0.62)	(-1.02)	(-0.98)	(-0.63)	(-1.04)
ΔR_t^{stoxx}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.03)	(0.96)	(0.27)	(0.88)	(-0.64)	(-0.42)	(0.03)	(0.62)	(0.60)	(0.83)
$\Delta\sigma_t^{stoxx}$	0.01	0.02	0.01	0.03	0.00	0.03	0.02	-0.02	0.06	0.03
	(0.32)	(0.63)	(0.25)	(0.72)	(0.07)	(0.89)	(0.63)	(-0.38)	(1.70)	(0.96)
ΔLiq_t	0.00	0.00	0.00	-0.01	0.01	0.00	0.01	0.00	0.00	0.00
	(-0.81)	(0.49)	(0.84)	(-1.07)	(1.21)	(0.28)	(0.87)	(0.41)	(-0.31)	(0.14)
$\Delta Exch_t$	0.00	0.00***	0.00***	0.00**	0.00**	0.00*	0.00***	0.00	0.00**	0.00**
	(-1.36)	(-2.74)	(-2.94)	(-1.93)	(-1.94)	(-1.76)	(-3.47)	(-1.47)	(-2.28)	(-2.24)
Residual function										
ω	0.00	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00
	(-0.34)	(3.73)	(3.91)	(4.42)	(3.70)	(3.52)	(4.45)	(3.83)	(3.34)	(4.38)
ARCH(α)	2.11	0.06***	0.09***	0.13***	0.07***	0.07***	0.15***	0.11***	0.05***	0.14**
	(0.34)	(5.55)	(6.12)	(6.53)	(5.88)	(5.89)	(6.43)	(6.20)	(4.70)	(6.25)
GARCH(β)	0.94***	0.93***	0.90***	0.83***	0.91***	0.92***	0.81***	0.87***	0.93***	0.82***
	(153.78)	(83.44)	(64.09)	(38.51)	(69.85)	(73.83)	(34.27)	(45.92)	(80.44)	(34.18)
Student(v)	2.02***	3.96***	4.08***	4.49***	4.81***	4.10***	4.29***	4.49***	3.37***	4.12***
	(38.51)	(11.74)	(11.36)	(10.89)	(10.59)	(11.61)	(10.91)	(10.30)	(12.33)	(10.79)

Goodness of fit										
Log-Likelihood	6778	6706	6614	5953	6365	6336	6016	5907	5906	6264
AIC	-6.38	-6.31	-6.22	-5.60	-5.99	-5.96	-5.66	-5.56	-5.56	-5.89
DW	1.98	1.60	1.38	1.31	1.58	1.34	1.31	1.41	1.69	1.34

3.3. Model Comparison

Tables 8 and 9 respectively show the optimal fitting models of China and the U.S. credit spreads by grade, maturity, corresponding log-likelihood, DW statistics and Akaike information criterion (AIC) of the models.

Table 8: Optimal GARCH model of China credit spreads

	AAA	*AA*	*AA-*	*0-1Y*	*1-3Y*	*3-5Y*	*5-10Y*	*10+Y*
Optimal Model	EGARCH	EGARCH	PGARCH	PGARCH	PGARCH	PGARCH	PGARCH	EGARCH
Distribution	Student-t	Student-t	Student-t	Student-t	Student-t	Student-t	Student-t	Student-t
Log-Likelihood	-2376	-2761	-2680	-3084	-2677	-2647	-2502	-2591
DW	1.73	1.61	1.62	1.77	1.84	1.75	1.88	1.90
AIC	4.06	4.72	4.58	5.27	4.58	4.53	4.28	4.43

Table 9: Optimal GARCH model of the U.S. credit spreads

	AAA	*AA*	*A*	*BBB*	*1-3Y*	*3-5Y*	*5-7Y*	*7-10Y*	*10-15Y*	*15+Y*
Optimal Model	PGARCH	PGARCH	PGARCH	PGARCH	EARCH	PGARCH	PGARCH	PGARCH	PGARCH	PGARCH
Distribution	Student-t	Student-t	Student-t	Student-t	Student-t	Student-t	Student-t	Student-t	Student-t	Student-t
Log-Likelihood	6815	6715	6617	5956	6367	6340	6016	5915	5915	6269
DW	1.98	1.60	1.38	1.31	1.58	1.34	1.31	1.41	1.69	1.34
AIC	-6.41	-6.32	-6.22	-5.60	-5.99	-5.96	-5.66	-5.56	-5.56	-5.90

It can be seen from Table 8 that the goodness of fit of the asymmetric GARCH model (EGARCH, PGARCH) is better than that of the symmetric GARCH model (GARCH (1,1), GARCH-M). The parameters of the leverage effect are significant, indicating that there is an asymmetric effect of volatility both in China and US bond market (see External Appendix A-D).

Furthermore, according to the log-likelihood, AIC and DW statistic, we find that the GARCH models with Student's t-distribution fit credit spreads better than that of normal distribution, indicating that the "fated-tail distribution" can improve the accuracy of bond market volatility measurement. This finding applies both to China and the U.S., and is in line with Mcneil and Frey (2000)'s research on financial time series.

According to the above comparison of the GARCH family models, it is obvious that the EGARCH model and the PGARCH model are more suitable for modeling the corporate bond credit spreads of China and the U.S. In particular, from Table 8 and Table 9, we can see that PGARCH model performs better in credit spreads with a wider range of ratings and maturities compared with EGARCH model. It can be concluded that no matter it is in an emerging bond market (represented by China) or in a mature bond market (represented by the United States), the leptokurtosis and fated-tail effect are common in bond yield volatility.

4. INFLUENCING FACTORS OF CREDIT SPREAD

By comparing the parameters (See the EGARCH and PGARCH model in External Appendix) in the best-fitting model of China and the U.S. credit spreads, we analyzed the differences between the determinants of the two countries.

First, compared with the optimal GARCH model of the U.S., the optimal model of China has a larger positive constant. On the one hand, with the expansion of China bond market and the deepening of marketization in recent years, the probability of bond default has increased. On the other hand, the infrastructure has not been completed yet, and the inefficiency and frictions in the disposal of defaulted bonds make investors reluctant to hold corporate bonds. It might increase the risk premium of China corporate bonds relatively to the same rating of corporate bonds in the U.S.

We also find that China bond market is more likely to be affected by risk-free interest rates, showing a procyclical relationship between the changes in credit spreads and in risk-free interest rates. It suggests that when the market is in a period of “credit expansion”, declining risk-free interest rate drives the credit spread down, and the cost of corporate financing reduces as well. When the market is in “credit tightening” period, the credit spreads rise and the cost of corporate financing increases, further aggravating the financing difficulties of enterprises.

The volatility of stock market yield has a greater negative impact on changes in credit spreads in China than in the U.S. This may be attributed to the fact that Chinese investors have fewer financial products to invest in. As a result, when the stock market volatility increases, the bond market becomes a “safe haven” for Chinese investors, which would reduce corporate bond credit spreads.

In addition, the credit spreads of Chinese corporate bonds are more susceptible to liquidity factors. At present, the China bond market is still in the early stage of opening up, and there are still many restrictions on foreign investors. Foreign investors participating in China bond market through “Bond Connect”, Qualified Foreign Institutional Investors (QFIIs) and other channels, mainly invest in government bonds and policy bank bonds with the highest credit rating and maximal security. However, corporate bonds accounted for only 0.48% of the total bond holdings of foreign investors (collected from China Bond, by June, 2020). The lack of investors in the bond market and the preference of investors for riskless bonds may be the reason why liquidity risk has a more significant impact on China credit spreads. Correspondingly, the coefficient of the liquidity factor of the U.S. credit spreads is insignificant. The U.S. has the largest and most open bond market in the world, so its credit spreads are less affected by liquidity factors.

5. CONCLUSIONS

Based on standard normal distribution and Student's t-distribution, this paper compares the fitting goodness of GARCH family models (GARCH (1,1), GARCH-M, EGARCH, and PGARCH model) on changes in corporate bond credit spreads of China and the U.S. It also determines the optimal model for fitting their credit spreads. The empirical research corroborates that the estimation of credit spreads can be improved by using the asymmetric GARCH model and Student's t-distribution with features of leptokurtosis and fated-tail. Compared with the traditional GARCH model, the EGARCH model and PGARCH model based on the Student's t-distribution can better fit changes in credit spreads. This result is applicable to different credit ratings and different maturities of corporate bonds in both countries.

According to the optimal GARCH model, we have studied the determinants of credit spreads in China and the U.S. The intercept of China's credit spread change is significantly positive, which means China's credit spread is in an uptrend compared with the U.S. Furthermore, the China credit spreads are more likely to be affected by risk-free interest rates, stock market volatility and liquidity factors, considering that the coefficient of these factors are significant in the models of China while insignificant in most models of the U.S.

Based on the research on the Sino-US differences of credit spread determinants, we put forward several suggestions for the Chinese bond market. First, strengthen infrastructure construction. China has not established a market-denominated and legalized bond default mechanism. Investors' enthusiasm for participating in the bond market would increase if bond default processing costs are reduced and the interests of bondholders are protected effectively. Second, deeply open the bond market and introduce foreign investors. The opening up in the bond market will increase the liquidity of the domestic bond market, and reduce the liquidity cost for investors. Third, innovate corporate financing tools to reduce financing costs. We find that there is a procyclical relationship between credit spreads and risk-free interest rates. As a result, companies need innovative financial tools and efficient financial mechanisms to reduce financing costs under the "credit tightening" market conditions.

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