The volatility cluster character of corporate bond yield

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Abstract: - We chose weekly transaction data from 2011 to 2012 in Shenzhen and Shanghai Exchange platform, and the paper analyzed the volatility clustering effect of corporate bond yield spread mainly by using time series data. Firstly, the paper described the data character. Secondly, the paper analyzed the volatility cluster character of corporate bond yield by using Autoregressive Conditional Heteroskedasticity model. In the end, we did cointegration analysis. We found corporate bond yield have volatility cluster and asymmetric character. And investors could choose different corporate bonds with different yield volatility according to own analysis.

Key-Words: - corporate bond yield volatility cluster cointegration analysis

1 Introduction

There are many papers on volatility cluster character of corporate bond yield. Güntay(2010) found the significant relationship between corporate bond spreads and forecasting dispersion by using panel data^[1]. Miller (1977) proposed that bond prices mainly reflected optimistic investors' view for the constraint of short-term investment behavior, and his results indicated that the higher forecasting dispersion of analyst had a greater impact on credit spreads of listed companies^[2]. Dick-Nielsen(2010) presented the liquidity of corporate bonds before and after the financial crisis by using illiquidity method ^[3]. His empirical results showed that, when financial crisis began, bonds illiquidity increased significantly, and bond spread increased continuously and slowly. When the most important guarantor was seriously affected in the financial crisis, bonds liquidity became worse.

Bonds issued by financial institution stopped flowing during financial crisis. Bewley(2004) found stock markets volatility had significant effect on bond spread by using the implied volatility from option market and conditional heteroskedasticity of

The authors are grateful for research support from the National Natural Science Foundation of China (71103050); Research Planning Foundation on Humanities and Social Sciences of the Ministry of Education (11YJA790152); Planning Foundation on Philosophy and Social Sciences in Shenzhen City (125A002). equity market index, and the empirical results indicated that the implied volatility form option market had no significant effect on bond spread, but conditional heteroskedasticity of equity market index had significant and stable effect on bond spread, and bond spread had a decreasing trend with an increase in heteroskedasticity volatility^[4]. Campbell(2010) presented a regression model of both equity idiosyncratic volatility and equity yields, and analyzed that equity volatility had an effect on corporate bond yields by using panel data^[5]. His empirical results showed that equity idiosyncratic volatility had a strong relation with borrowing cost of issued corporate bonds, and also equity volatility explained short-term return changes of corporate bonds and long-term increasing trends of bond returns. This method could be used in our study.

Gemmill(2011) found that corporate bond spreads were mostly caused by default loss by using panel data regression and the contribution of systemic factors was lower when he took downside risk into account^[6]. He found that corporate bond spread exhibit a strong correlation with idiosyncratic risk: bond spreads correlate with idiosyncratic volatility and risk value of corporate bonds. Price spread of corporate bonds increased with an increase of bond idiosyncratic risk value, because bond idiosyncratic risks had left-skewness distribution trends. Elton (2001) examined risk premium of corporate bonds by using time series and cross-sectional data, and his empirical results showed that bond default was composed of lower bond spreads, but tax and systemic risk composed

higher corporate bonds spreads^[7]. Huang (2002) found, due to the launch of credit risk in corporate bond spreads by using structural model with default factor, that credit spreads account for a smaller part of short-run corporate bonds, and a bigger part of junk bonds^[8]. Tang(2010) studied the interaction of market risk and default risk in credit spread of corporate bond by using the newest structural model^[9]. He found that, when GDP increased, average credit spread decreased, but GDP growth volatility and equity market jump risk increased by using swap spread of credit default to estimate. He proved that default risk was the main part of credit spread, and macroeconomic variables took up a small part. Based on Fama-French model, Gebhardt(2005) found that, after controlling duration, credit ratings, maturity and other variables, bond cross-section yields had strong correlation with default probability. When control default risk and period factors, bond maturity had a correlation with bond yield^[10]. Also Huang(2013) Reviewed on foreign study of corporate bond spread^[19]. Wang and Huang(2013)also analyzed corporate bond yield character in china bond market^[20]. Meanwhile Huang(2013) studied the factors which affected corporate bond yield spread^[21]. Huang(2013) analyzed the term structure of Chinese corporate bond yields^[22]. Huang(2013) researched on liquidity risk premium based on bond age, and found that bond liquidity risk affect corporate bond volatility character^[23]. Huang(2013) analyzed on the influence of Fama-French factors in equity and bond markets on corporate bond spread^[24]. The study above assured the volatility in bond yield, and we will find the volatility in Chinese bond market.

Merton (1974) initiated the modern analysis of corporate debt by pointing out that the holders of risky corporate bonds can be thought of as owners of riskless bonds who have issued put options to the holders of the firm's equity^[25]. When volatility increases, the value of the put options increases, and it will benefit equity holders at the expense of bondholders. The volatility which is relevant for option value, and thus for corporate debt, is total firm volatility, including both idiosyncratic volatility and systematic or market-wide volatility. This is important because idiosyncratic volatility can move very differently from market-wide volatility. In particular, Campbell et al. (2001) point out that idiosyncratic volatility has trended upwards since the mid-1970s, while market-wide volatility has undergone temporary fluctuations but no trend increase^[26]. The findings of Campbell et al. suggest that increasing idiosyncratic volatility could have depressed corporate bond prices and supported corporate equity prices, during the past few decades and during the late 1990s in particular. The mechanism for creating volatility clusters may be a memory, nonlinear coupling between the price and agent parameters or the herding effect. The latter may be achieved by a next neighbour interaction as in statistical mechanics or explicitly in the dynamics. Mixed GARCH-Jump modeling has emerged as a powerful tool to describe the dynamics of asset returns in discrete-time. Recent work in this area by, for example, Duan et al.(2005, 2006) and Maheu and McCurdy (2004) allows for time-variation in the jump component of the mixed GARCH-Jump model^[27,28,29]. In particular, Duan et al. develop a constant intensity NGARCH-Jump model that allows for time-variation through a common GARCH multiplier in the "diffusion" and jump component. In the limit, their discrete time model can converge to continuous-time jump-diffusion processes with jumps in the stochastic volatility. They find that the NGARCH-Jump model provides a better fit for the time-series of S&P 500 index to the returns relative normal NGARCH specification. Maheu and McCurdy develop a mixed GARCH-Jump model that admits separate timevariation and clustering in the jump intensity, but does not accommodate for volatility feedback in the jump component. When applied to individual stocks and indices in the US, their model outperforms the GARCH-Jump model with constant intensity and i.i.d. jump component. These findings give rise to the question which jump structure best fits the asset return dynamics under an asymmetric GARCH specification. Is it volatility feedback in the jump component, autoregressive jump intensity, or a combination of both? Should volatility feedback in the jump component be generated through a common GARCH multiplier or a separate measure of volatility in the jump intensity function? Harvey (1995) and Bekaert and Harvey (2002) argue that emerging market returns have higher volatility, fatter tails, and greater predictability. In contrast to the mature markets, Bekaert and Harvey(1997) show that volatilities in emerging markets are determined by local information primarily variables^[30]. Aggarwal et al. (1999) find that the volatilities in emerging markets exhibit large and sudden shift^[31]. They find that these jump-like changes in the emerging markets' volatility are primarily associated with important local events. Aggarwal et al. also find that most emerging markets' returns show positive skewness, which is in contrast to the negative skewness in developed markets. Some scholars found idiosyncratic volatility effect on bond yield spread, we can also

find whether there is the same effect on corporate bond yield.

One existing explanation on asymmetric volatility is based on the "volatility feedback effect". When the agents face a price change more than expected, they revise their estimated variance upward, indicating an increase in uncertainty. This requires a greater risk premium and a lower price, other things equal. When the price increases more than expected, its rise will be muted; when the price decreases more than expected, its decline will be intensified. Campbell and Hentschel also show that clusters, because the exogenously volatility specified dividend process clusters. However, Schwert presents that there is a weak link between macroeconomic fundamentals and volatility. The shock on fundamentals, like a dividend, would not be related to the volatility puzzles. Thus, the paper has not successfully explained both volatility puzzles simultaneously. MacQueen and Vorkink give an endogenous explanation both on asymmetric volatility and volatility clustering. They propose a preference-based equilibrium asset pricing model where the origin of the volatility clustering is time-varying investors' and autocorrelated sensitivity to the news. They argue that volatility is persistent, because the sensitivity is autocorrelated, and it tends to be asymmetric due to the volatility feedback effect. The study above analyzed on volatility and bond yield, and we will find whether there is volatility cluster effect on corporate bond yield in our paper below.

According to their study, many factors affected corporate bond yields, and analysts found these factors change the corporate bond yield volatility cluster character. In the paper, we would mainly study on the volatility cluster character of corporate bond yield in Shenzhen transaction market and Shanghai transaction market.

2 Data Description

Since 2007 SHANGHAI stock exchange had corporate bond transaction data, and SHENZHEN stock exchange had corporate bond transaction data since 2008. Between the year 2007 to 2010, SHANGHAI stock exchange and SHENZHEN stock exchange only had several bonds and the amount ranged. Because the sample was small, and according to statistics in 2011 there were only 25 corporate bonds which matched conditions, and in 2012 there were 54 corporate bonds which matched conditions. In consideration of data continuous and comprehensive and representative, in the paper we chose corporate bond transaction data from January 1st 2012 to December 31st 2012. In the paper we got rid of corporate bonds which were unmatched to treasury bonds and corporate bonds that had less than 1 year to maturity, for the reason that corporate bonds which had less than 1 year to maturity would more sensitive to interest rates.

By screening finally we got 54 corporate bonds, and these corporates had enough sample data. Because corporate bonds transaction was less frequent, and the data was small, if we chose transaction data of everyday, there was less data, and if chose transaction data of every month, the data would be too small. In the end, according to foreign literatures, in order to get continuous data, we chose nearly 50 corporate bonds weekly transaction data from December 2011 to December 2012.

We got data from Wind database, and the bonds had simple interest, fixed rate. According to Duffee(1998), we divided the bonds into three categories, including short term bonds with 2 to 7 years maturity^[11]; median bonds with 7 to 10 years maturity; long term bonds with maturity more than 10 years. In the paper, most of the bonds were short term and median term, also some were long term. And the bonds could be divided into AAA, AA+ and AA three ratings. The sample contained Manufacturing industry, Power industry, Building industry, Mining and Quarrying industry, Transportation industry, Real Estate and Service industry. The sample covered almost all the industries.

3 Descriptive Statistics

From table 1-1, we could see the average yield of three-year period corporate bonds is 5.676993, and the median value is 5.407333, and the maximum value is 6.834300, and minimum value is 4.817567, and the standard deviation is 0.628778, and it doesn't obey normal distribution in the 10% confidence level.

The average yield of five-year period corporate bonds was 5.600183, the median value was 5.365403, and the maximum value was 6.809523, and the minimum value was 4.612938, and the standard deviation was 0.659730, and it didn't obey normal distribution in 10% confidence level.

The average yield of seven-year period corporate bonds was 5.923490, and the median value was 5.824601, and the maximum value was 6.743102, and the minimum value was 5.193502, and the standard deviation was 0.470744, but it obeyed normal distribution. The average yield of ten-year period corporate bonds was 4.203931, and the median value was 4.649821, the maximum value was 5.458503, and the minimum value was 1.435926, and the standard deviation was 1.027382, and it didn't obey normal distribution in 1% confidence level. From the four series, we found the ten-yield period corporate bonds fluctuate the most strongly.

Table 1-1 Descriptive statistics of corporate bonds with maturity of 3, 5, 7, 10 years

maturity of 5, 5, 7, 10 years					
	Y3	Y5	Y7	Y10	
Average	5.676993	5.600183	5.923490	4.203931	
Median	5.407333	5.365403	5.824601	4.649821	
Maximum	6.834300	6.809523	6.743102	5.458503	
Minimum	4.817567	4.612938	5.193502	1.435926	
St.	0.628778	0.659730	0.470744	1.027382	
Skewness	0.635593	0.576595	0.370223	-1.480726	
Kurtosis	2.026414	1.905184	1.917341	4.119797	
JB	5.448044*	5.372992*	3.655872	21.301310***	
Р	0.065610	0.068119	0.160745	0.000024	

* denotes statistical variables are significant on the 10% confidence level, *** denotes statistical variables are significant on the 1% confidence level.

4 Corporate bond yield characteristic analysis based on conditional heteroskedasticity

The paper analyzed volatility cluster of corporate bond yield by using the model, and analyzed whether it had asymmetry.

4.1 ARCH model

Engle(1982) presented the model, and Bollerslev(1986) expanded the model, and got $GARCH \mod l^{[12,13]}$.

Building the model as bellow:

$$y_t = r_0 + r_1 x_{1t} + \dots + r_k x_{kt} + u_t \tag{1-1}$$

$$E_{t-1}(y_t) = r_0 + r_1 x_{1t} + r_2 x_{2t} + \dots + r_k x_{kt}$$
(1-2)

$$var\left(y_{t} \middle| Y_{t-1}\right) = E_{t-1}(y_{t} - r_{0} - r_{1}x_{1t} - \dots - r_{k}x_{kt})^{2} = E_{t-1}u_{t}^{2}$$
(1-3)

 u_t^2 obeys AR(1) process:

$$u_t^2 = a_0 + a_I u_{t-I}^2 + \varepsilon_t \tag{1-4}$$

In equation (1-4), ε_t was white-noise process, and it satisfied:

$$E(\varepsilon_t) = 0 \tag{1-5}$$

$$E(\varepsilon_t, \varepsilon_s) = \begin{cases} \emptyset^2, & t=s \\ 0, & t\neq s \end{cases}$$
(1-6)

So, the conditional distribution of disturbing term u_t was,

$$u_t \sim N\left[0, (a_0 + a_1 u_{t-1}^2)\right]$$
 (1-7)

ARCH(p) could be presented as below:

$$var(u_t) = \sigma_t^2 = a_0 + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + \dots + a_p u_{t-p}^2$$
(1-8)

$$1 - a_1 z - a_2 z^2 - \dots - a_p z^p = 0 \tag{1-9}$$

If $a_i(i=1,2,...,p)$ were all negative, equation (1-9) was equal to $a_1+a_2+...+a_p < l$

$$\operatorname{var}(u_t) = \sigma^2 = a_0 \tag{1-10}$$

4. 2 GARCH model

Building model as below:

$$y_t = x'_t \times \gamma + u_t$$
 $t = 1, 2, ..., T$ (1-11)
 $\sigma^2 = \omega + \alpha u^2 + \beta \sigma^2$ (1.12)

$$\sigma_t^{\tau} = \omega + \alpha u_{t-1}^{\tau} + \beta \sigma_{t-1}^{\tau} \tag{1-12}$$

In the equation, $x_t = (x_{1t}, x_{2t}, ..., x_{kt})'$ was explaining variable vector, and $\gamma = (r_1, r_2, ..., r_k)'$ was coefficient vector.

$$l_t = -\frac{l}{2} ln(2\pi) - \frac{l}{2} ln\sigma_t^2 - \frac{l}{2} (y_t - x_t' \gamma)^2 / \sigma_t^2$$
(1-13)

In equation

$$\sigma_{t}^{2} = \omega + \alpha (y_{t-1} - x_{t-1}^{'} \gamma)^{2} + \beta \sigma_{t-1}^{2}$$
(1-14)

$$\sigma_t^2 = \frac{\omega}{(1-\beta)} + \alpha \sum_{j=1}^{\infty} \beta^{j-1} u_{t-j}^2$$
(1-15)

$$u_{t}^{2} = \omega + (\alpha + \beta)u_{t-1}^{2} + v_{t} - \beta v_{t-1}$$
(1-16)

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta z_t$$

$$\tau = |\mathbf{x}|$$
(1-17)

 $z_t = |x_t|$ High level GARCH model could have any number of ARCH items and GARCH items, and it can be written GARCH(q,p). It's conditional variance could be expressed as:

$$\sigma_t^2 = \omega + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i u_{t-i}^2 = \alpha_0 + \alpha(L) u_t^2 + \beta(L) \sigma_t^2$$

$$(1-18)$$

$$\sigma_t^2 = \theta_0 + \theta(L) u_t^2$$

$$(1-19)$$

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{1-20}$$

4.3 Unsymmetrical ARCH model

Engle and Ng(1993) first presented it. For corporate bond market^[14], investors reacted to favorable news less strongly than to bad news.

4.4 TARCH model

Zakoian(1990) and Glosten (1993) firstly got the model as $below^{[15,16]}$:

$$\sigma_t^2 = \omega + \alpha \times u_{t-1}^2 + \gamma \times u_{t-1}^2 d_{t-1} + \beta \times \sigma_{t-1}^2$$
(1-21)
In the equation downway variable when

In the equation, d_{t-1} was dummy variable, when $u_{t-1} < 0$, $d_{t-1} = 1$ or else $d_{t-1} = 0$. Only if $\gamma \neq 0$.

$$\sigma_t^{1-1} = \omega + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i u_{t-i}^2 + \sum_{k=1}^r r_k u_{t-k}^2 d_{t-k}$$
(1-22)

4.5 EGARCH model

Nelson(1991) firstly got the model as below^[17]:

$$ln(\sigma_t^2) = \omega + \beta ln\left(\sigma_{t-1}^2\right) + \alpha \left|\frac{u_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}} \quad (1-23)$$
$$ln(\sigma_t^2) = \omega + \sum_{j=1}^q \beta_j ln\left(\sigma_{t-j}^2\right) + \sum_{i=1}^p \alpha_i \left|\frac{u_{t-i}}{\sigma_{t-i}} - E\left(\frac{u_{t-i}}{\sigma_{t-i}}\right)\right| + \sum_{k=1}^r r_k \frac{u_{t-k}}{\sigma_{t-k}} \quad (1-24)$$

$$ln(\sigma_t^2) = \omega + \beta ln\left(\sigma_{t-1}^2\right) + \alpha \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}}$$
(1-25)

4.6 PARCH model

Ding et al.(1993) expanded it, and built PARCH model. The conditional variance equation as below^[18]:

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^q \beta_j \sigma_{t-j}^{\delta} + \sum_{i=1}^p \alpha_i \left(\left| u_{t-i} \right| - \gamma_i u_{t-i} \right)^{\delta} \quad (1-26)$$

In the equation: $\delta > 0$, when $i=1,2, \dots, r$, then $|r_i| \le l$, when i > r, then $r_i = 0, r \le p$

4.7 Asymmetrical information impulse curve In the conditional variance equation of EGARCH model

$$ln(\sigma_t^2) = \omega + \beta ln\left(\sigma_{t-1}^2\right) + \alpha \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}}$$
(1-27)

Supposing residual u_t obeys normal distribution. If set

$$f\left(\frac{u_{t-l}}{\sigma_{t-l}}\right) = \alpha \left|\frac{u_{t-l}}{\sigma_{t-l}}\right| + \gamma \frac{u_{t-l}}{\sigma_{t-l}}$$
(1-28)

 $z_t = u_t / \sigma_t$, then $f(z_t) = \alpha |z_{t-1}| + \gamma z_{t-1}$

It linked correction of conditional volatility and impulse information u_{t-1} . When $u_{t-1} > 0$, then $\frac{\partial f}{\partial z_{t-1}} = \alpha + \gamma$, when $u_{t-1} < 0$, $\frac{\partial f}{\partial z_{t-1}} = \alpha + \gamma$, f(.) contained asymmetric effect.

In the paper, we chose the GARCH model to analyze the volatility cluster character of corporate bond yield because it could better reflect the data character. Also, we chose TARCH model to analyze the asymmetric character of corporate bond yields. The two model is the best for our analysis.

5 Analysis on volatility cluster of corporate bond yields

The paper analyzed on volatility cluster of corporate bond yields. We could see the results in figure 3-1, and the vertical axis showed average value of corporate bond yield, and horizontal axis meant the week. We could see that the biggest value of average corporate bond yield was nearly 7.5, and it's in 40th week 2011. Then, it fell to 5.8 in 45th week 2011, and sooner or later, it rose up to 6.5, but after 60th week, it quickly fell, in 79th week, it fell to less than 5.0, and it's the least value. Although it rose later, but the corporate bond average value kept less than 6.0 until the 102th week.

In all, the average yield of corporate bond fluctuated heavily, and from the chart we could see, the weekly average yield of corporate bond fluctuate heavily after big fluctuation, and it fluctuate softly after small fluctuation.



Fig. 1-1 Corporate bond average yields chart

(1-29)

5.1 Random walk model

In the paper we built a random walk model of corporate bond yield as below

$$yield_t = C_0 + C_1 yield_{t-1} + \varepsilon_t \tag{1-30}$$

Table 1-2 showed estimated results of the random walk model. From the table we could see the F value was significant on 1% confidence level, and it meant the model was significant. R-squared=0.941758, meant the equation fitted the real value good. But the constant term wasn't significant, and the coefficients of explaining variable YIELD(-1) were close to 1. The results meant that yield series followed a random walk process without drafting term, or the corporate bond yield followed a random walk process with average value zero.

Table 1-2 Random effect test results

variables	coefficients	Std.	t	Prob.
С	0.148327	0.139893	1.060285	0.2916
yield(-1)	0.973680***	0.024336	40.01015	0.0000
R2	0.941758	Log	45.11183	
		likelihood		
AIC	-0.853700	SC	-0.80192	
F	1600.812***	Prob	0.000000	

*** denotes statistical variables are significant on the 1% confidence level.

 $yield_t = 0.973680 yield_{t-1} + \varepsilon_t \tag{1-31}$

t statistics = (0.024336)

Log likelihood=45.11183, AIC=-0.853700, SC=-0.801915.

From figure 1-2 we could see, the vertical axis meant residual, and the horizontal axis meant which week. The residuals of regression equation turned volatility cluster, and the big fluctuation would continue for a while, also the little fluctuation would continue for a while. In the figure, the fluctuation in 43th week was big, also in 44th week and 45th week. In 72th week, there's a little fluctuation, and a little fluctuation came behind it.

.8 .6 .4 .2 -.2 -.4 -.6 20 50 10 30 40 60 70 80 90 100

Fig. 1-2 Residual sequences chart

From figure 1-3, we could see some part of autocorrelation function of square residual excessed the 95% confidence level. Statistically it was not zero, also the Q value was significant, and the corresponding probability was less than 0.01. So the square residual of equation (1-31) existed autocorrelation. It has ARCH effect.

RESID01

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Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
· 🗖		1	0.435	0.435	19.696	0.000
' Þ		2	0.182	-0.009	23.183	0.000
ı þi		3	0.053	-0.029	23.477	0.000
וןו		4	0.026	0.018	23.548	0.000
ים	ים ו	5	0.107	0.116	24.785	0.000
νÞ	'P'	6	0.204	0.143	29.327	0.000
		7	0.331	0.223	41.436	0.000
יףי		8	0.100		42.545	0.000
		9	0.009		42.554	0.000
וןי	יםי	10	0.043	0.090	42.767	0.000
וןו	י םי	11	-0.049		43.046	0.000
יםי	' '	12	-0.107		44.385	0.000
101		I	-0.064		44.872	0.000
1	[14	-0.025	-0.036	44.945	0.000
10		15	-0.060		45.375	0.000
יםי	[16	-0.067	-0.032	45.931	0.000
	ון ו	17	0.017	0.065	45.969	0.000
יםי	וםי	18	-0.104	-0.078	47.330	0.000
יםי		19	-0.139	0.002	49.788	0.000
יםי		20	-0.120	-0.039	51.635	0.000
ι[ι		21	-0.075	0.021	52.368	0.000
יםי	וםי	22	-0.106	-0.067	53.858	0.000
יםי	יםי	23	-0.131	-0.086	56.159	0.000
יםי	ן וםי	24	-0.099	-0.061	57.490	0.000
1 1		25	-0.003	0.194	57.491	0.000
ι¢ι	ı[ı	26	-0.070	-0.119	58.177	0.000
ι¢ι	1	27	-0.058	-0.034	58.643	0.000
ı þi		28	0.078	0.236	59.513	0.000
I 🛛 I	ים ו	29	-0.036	-0.090	59.697	0.001
I 🛛 I	111	30	-0.041	-0.023	59.939	0.001
ι¢ι	ו מי ו	31	-0.090	-0.084	61.152	0.001
I 🛛 I	111	32	-0.029	-0.010	61.276	0.001
ι¢ι	10	33	-0.086	-0.061	62.417	0.001
ιĮι	ו מי ו	34	-0.081	-0.096	63.448	0.002
I 🛛 I	ıd ı	35	-0.027	-0.132	63.565	0.002
ι¢ι	ı þi	36	-0.053	0.078	64.016	0.003

Fig. 1-3 Squared residual correlation diagram

5.2 ARCH model and GARCH model analysis

On the first place, we built a conditional variance equation, and it could fit GARCH (1,1) model below.

$$\sigma_t^2 = \alpha_0 + \alpha_I \varepsilon_{t-I}^2 + \beta_I \sigma_{t-I}^2$$
(1-32)

To ensure that the conditional variance is nonnegative, we usually required statistic parameters nonnegative, and required $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta_1 > 0$. Also when coefficient statistics $\hat{\alpha}_1 + \hat{\beta}_1 < 1$, the conditional variance of yield would run to unconditional variance $\frac{\alpha_0}{1 - \alpha_1 - \beta_1}$.

From table 1-3 we could see, in the conditional equation, the estimated value of parameter C was 4.23E-05, but it was not significant. The coefficient of RESID(-1) 2 was 0.326536, and it was significant on 5% confidence level. The coefficient of GARCH(-1) was 0.661261, and it was significant on 1% confidence level, and all of the parameters were positive, so it followed the nonnegative required of conditional variance, and followed the parameter require of GARCH model. The sum of coefficients for ARCH and GARCH were: $\hat{\alpha}_1 + \hat{\beta}_1 = 0.326536 + 0.661261 < 1$, and it followed the GARCH restrict, the variance was convergent at $\sigma^2 = \frac{\hat{\alpha}_0}{I - \hat{\alpha}_I - \hat{\beta}_I}$. It meant the historical impulse would insist for a while, and it could expect the future.

Table 1-3 GARCH(1, 1) model test results

variables	coefficients	Std.	Z	Prob.
С	4.23E-05	3.20E-05	1.321265	0.1864
RESID(-	0.326536**	0.163007	2.003199	0.0452
1)^2				
GARCH(-	0.661261***	0.126927	5.209790	0.0000
1)				
R-squared	0.943883	Log	241.7816	
_		likelihood		
AIC	-4.708547	SC	-4.60498	

** denotes statistical variables are significant on the 5% confidence level, *** denotes statistical variables are significant on the 1% confidence level.

5.3TARCH model analysis

TARCH model also meant GJR model, and the model was joined with additional item which explained possible existing asymmetry.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$$
(1-33)

$$I_{t-1}$$
 was dummy variable, and $(1, \varepsilon_{t-1} < 0)$

 $I_{t-1} = \begin{cases} 0, & \varepsilon_{t-1} > 0 \end{cases}$ From equation (1-33) we could see $\varepsilon_{t-1} > 0$ and $\varepsilon_{t-1} < 0$ affect σ_t^2 , and the results were $\alpha_1 \varepsilon_{t-1}^2$ and $(\alpha_1 + \gamma)\epsilon_{t-1}^2$. For conditional variance, the nonnegative requires were $\alpha_0 \ge 0$, $\alpha_1 \ge 0$, $\beta_1 \ge 0$ and $\alpha_1 + \gamma \ge 1$. If $\gamma = 0$, then there wasn't asymmetric effect, and if $\gamma > 0$, then there was asymmetric effect.

Table 1-4 TARCH model test results

Table 1-4 Tracer moder test results						
variables	coefficients	Std.	Z	Prob.		
С	4.23E-05	3.23E-05	1.313152	0.1891		
RESID(-1) ²	0.309236*	0.174230	1.774873	0.0759		
RESID(-	0.034913	0.187957	0.185751	0.8526		
$1)^{2}$ (RESID (-						
1)<0)						
GARCH(-1)	0.662819***	0.126860	5.224796	0.0000		
R-squared	0.943867	Log	241.7979			
		likelihood				
AIC	-4.689067	SC	-4.55961			

* denotes statistical variables are significant on the 10% confidence level, *** denotes statistical variables are significant on the 1% confidence level.

From table 1-4 we could see the coefficient of RESID(-1)2*(RESID(-1)<0) was 0.034913, and it wasn't significant, so we could infer there wasn't asymmetric effect.

Bewley(2004) got the similar results by using foreign data. Some scholar in the first section also study on idiosyncratic volatility on bond yield spread, and it gets similar results with our study.

The above analysis meant there was volatility cluster character for corporate bond yield, and when it was affected by other factors, the yield fluctuation would insist for a while.

6 Conclusion

We tested volatility cluster character of corporate bond yield spread by using Heteroscedasticity model like ARCH, GARCH and GRANGER. The 3 years, 5 years and 7 years corporate bond had the similar yields, and they were stable, but the 10 years corporate bond yield fluctuated heavily. As corporate bond terms increased, uncertainty increased, and corporate bond yield volatility increased, and this agreed with expected financial theory. Our analysis meant there was volatility cluster character for corporate bond yield, and when it was affected by other factors, the yield fluctuation would insist for a while.

In all, average corporate bond yield fluctuated heavily during sample periods. For weekly average yield the big volatility went with big volatility, and small volatility went with small volatility. We found corporate bond yield had volatility cluster character, and also it's asymmetric. Investors could choose different corporate bonds according to own analysis. Investors who preferring risk could choose corporate bonds that volatility more often, also risk aversion investors could choose corporate bonds that volatility less.

Also, there are some limitations in our paper, such as the more data will be better for the study, also, our study is quite simple, and we can do further research later.

Because of time limit, we could study on the following areas. We can study whether corporate bond yields affected by other things such as bond age and so on.

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