Chapter 7
Market Based Credit Rating and Its Applications

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Abstract Credit rating plays a critical role in financial risk management. It is like a name tag of a firm indicating its health condition. Generally, ratings involve a lot of firm-specific information which is hard to obtain or only available quarterly. In this chapter, we propose a two-step algorithm involving ARIMA-GARCH modelling and clustering to obtain a market based credit rating utilizing easily obtained public information. The algorithm is applied to 3-year CDS spreads of 247 publicly listed firms. Empirical result of the application and comparisons between the obtained ratings with the ratings given by agencies show that such a market based credit rating performs quite well.

7.1 Introduction

Credit rating is a reflection of a firm's creditworthiness, traditionally provided by professional rating agencies. It is widely used to measure the credit risk of a company, i.e. the firm's ability to meet its debt servicing obligations, and hence plays a significant role in the financial market. Investors can use credit ratings to aid their investment decisions, e.g., Erlenmaier (2011), while an issuer may use the rating to determine the optimal amount of debt outgoing or signal its low investment risk, e.g., Nordberg (2010). Some investment funds may restrict investing only on firms whose credit ratings exceed certain level.

In the past decades, more and more researchers are interested in credit ratings, especially after the 2008 subprime financial crisis. Some are interested in the effectiveness of agency's ratings. For example, Kliger and Sarig (2000) showed that the credit rating can provide better assessment of default risk than publicly-available information alone. Hull et al. (2004) discussed the relationship between bond yields,

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Credit Default Swap spreads, and credit rating announcements. Others are interested in proposition or replication of the ratings by the agencies. Altman (1968) used five financial ratios to predict bankruptcy, and many researchers employed the same financial variables based method to quantify credit risk, such as Kaplan and Urwitz (1979), Ederington (1985) and Kamstra et al. (2001). This approach often involves substantial firm-specific information which is hard to obtain or only available quarterly. Recently, Creal et al. (2014) proposed a market-based credit rating which makes direct use of the prices of traded assets. The basic idea of market-based credit rating is that asset prices of traded firms should reflects timely the publicly-available firm-specific information. Following the same idea, we propose a market-based credit rating method using CDS spreads and/or their robustified values. The proposed method is easy to understand and use. As a matter of fact, the ratings are easily reproducible.

Credit Default Swap (CDS) is a financial agreement between a buyer and a seller in which the buyer makes periodic payments to the seller and receives a payoff from the seller in exchange if the reference entity defaults before the CDS contract expires. CDS is widely used with other financial derivatives to hedge the risk or to speculate on price movements. The periodic payment the buyer makes, which is also known as the price of CDS, is quoted in spread. Higher spread means the referred entity has a higher possibility to default from market's perspective, indicating its lower creditworthiness. Ericsson et al. (2009) shows that firm leverage, which is closely related to default risk, plays a significant role in determining its CDS spread. Micu et al. (2004) also find that rating changes can cause dynamic shifts on CDS markets. Therefore, there should be a close relation between credit rating and CDS spread. In this chapter, we leverage this close relationship and show that the proposed credit rating based on CDS spreads works well in comparison with the results provided by rating agencies.

The rest of the chapter proceeds as follows. In the next section, we introduce the methodology used. In Sect. 7.3, we consider empirical analysis and provide some discussions. The concluding remarks are presented in Sect. 7.4.

7.2 Methodology

Different from the method of Creal et al. (2014), the proposed method uses a two-stage procedure: forecasting and clustering. Our goal is to make the market-based credit rating easy to follow and use. In particular, no special program is needed. The proposed method can be easily reproduced. On the other hand, unlike Creal et al. (2014), we do not consider ratings of firms that have no CDS data.

7.2.1 Modeling and Forecasting

Assume that we have time series of daily CDS spreads of N firms. Denote the data by $\{y_{it} | i = 1, \ldots, N; t = 1, \ldots, T\}$. These series have the same maturity. In our empirical analysis, we use 3-year CDS spreads.

Instead of using y_{it} directly, we use predictions in the proposed credit rating method. Rating is necessarily concerning future performance of a firm. Thus, it makes sense to use predictions. In our empirical analysis, we use 1-step ahead predictions. If preferred, multi-step predictions can be used. Another reason for using predictions is to mitigate the impact of outliers. Since firm's creditworthiness typically does not change overnight, an abrupt change in CDS spread might be caused by reasons not related to the fundamentals of a firm. Using predictions can mitigate the impacts of such isolated outlying observations.

The proposed rating method uses predictions of the level and volatility of a CDS time series. To obtain the predictions, we apply ARIMA-GARCH models to each CDS time series. The model entertained can be written as

$$z_{it} = (1 - B)^{d_i} y_{it}, \tag{7.1}$$

$$z_{it} = \sum_{j=1}^{p_i} \phi_j z_{i,t-j} + a_{it} + \sum_{j=1}^{q_i} \theta_j a_{i,t-j}, \tag{7.2}$$

$$a_{it} = \sigma_{it} \epsilon_{it}, \tag{7.3}$$

$$\sigma_{it}^2 = \alpha_{i,0} + \sum_{j=1}^{r_i} \alpha_{i,j} a_{i,t-j}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2, \tag{7.4}$$

where d_i is a nonnegative integer denoting the order of differencing, p_i and q_i are nonnegative integers representing the autoregressive (AR) and moving-average (MA) order of the differenced series z_{it}, respectively, $\{\epsilon_t\}$ is a sequence of independently and identically distributed random variates with mean zero and variance 1, r_i and s_i are also nonnegative integers indicating the autoregressive conditional heteroscedastic (ARCH) order and the generalized ARCH order, respectively. The distribution of ϵ_t can be Gaussian or standardized Student-t or some skewed distributions with heavy tails. Equations (7.1) and (7.2) are referred to as the *mean equations* for y_{it} whereas Eqs. (7.3) and (7.4) are the *volatility equation*. This class of model is general and applicable to the CDS time series. The parameters of the model in Eqs. (7.2) and (7.4) are estimated by the maximum likelihood method.

There are several R packages available for building an ARIMA(p, d, q)-GARCH(r, s) model for a given financial time series. See, for instance, the `fGarch` and `rugarch` packages. The latter package allows for fractional differencing, i.e., d_i of Eq. (7.1) may assume nonnegative real values.

The modeling steps used in this chapter are as follows:

1. Mean equation: For given maximum values of p, d and q, we use the Akaike information criterion (AIC) to select the order (p_i, d_i, q_i) for the time series y_{it}.

As a matter of fact, one can even apply the automatic model selection procedure `auto.arima` of the R package `forecast` to select ARIMA model.

2. ARCH test: Let $\hat{a}_{it}$ be the residual series of the mean equation. We apply Ljung-Box $Q(m)$ statistics to the squared series a_{it}^2 to detect the existence of conditional heteroscedasticity, also known as the ARCH effect. Under the null hypothesis of no conditional heteroscedasticity, the test statistic is distributed asymptotically as χ_m^2.
3. Volatility equation: If the ARCH effect is statistically significant, we entertain ARIMA(p_i, d_i, q_i)-GARCH(r_i, s_i) models with given maximum values r and s for the GARCH model. Again, AIC is used to select the GARCH order and the distribution of ϵ_{it}. If the ARIMA order can be reduced as a result of the joint estimation, we further simplify the mean equation. Again, the modification is carried out using the AIC.

Our choice of AIC is for simplicity. Other information criteria can be used if needed.

Once an ARIMA-GARCH model is built for the CDS time series y_{it}, we use the model to obtain predictions of y_{it} and its volatility. The forecast origin is the sample size T. Denote the h-step ahead forecasts of mean and volatility of y_{it} at the forecast origin T by $\boldsymbol{x}_i(h) = (\hat{y}_{i,T}(h), \hat{\sigma}_{i,T}(h))'$. Let $\boldsymbol{X}_h$ denote the collection of h-step ahead forecasts of mean and volatility at the forecast origin T for all time series. Specifically, the i-row of $\boldsymbol{X}_h$ consists of $\boldsymbol{x}_i(h)$. We use $\boldsymbol{X}_h$ in the proposed credit rating method.

7.2.2 Clustering

Clustering analysis has a long history in the statistical literature. Many methods are available, including agglomerative hierarchical methods, K-means, tree-based methods, and supporting vector machine. In this chapter, we use mainly the K-means for its wide applicability and nonparametric nature. We also apply a tree-based method in our discussion.

Consider the predictions in $\boldsymbol{X}_h$, which contains the mean and volatility of CDS spreads. Intuitively, a high-quality company would have low values in mean and volatility, and higher values in either mean or volatility are indicative of higher default risk. For ease in notation, we shall omit the subscript h and denote the predictions as $\boldsymbol{X}$ with ith row being $\boldsymbol{x}_i$.

Assume that there are k categories in the rating system. The K-means method uses some measurement of similarity between companies. In this chapter, we use the Euclidean distance to measure similarity. The basic idea of the K-means method is that the distances between members of a cluster should be as small as possible, but the total distance between the clusters is large. Let $\boldsymbol{S} = \{S_i | i = 1, \ldots, k\}$ denote the k clusters, and $\boldsymbol{m}_i$ be the mean vector of members in cluster S_i. The K-means method can be described as

$$\arg\min_{\boldsymbol{S}} \sum_{i=1}^{k} \sum_{\boldsymbol{x}\in S_i} \|\boldsymbol{x} - \boldsymbol{m}_i\|^2.$$

A company is assigned to one and only one cluster. There are various algorithms available to achieve K-means clustering. We describe briefly an algorithm below. Randomly select k points from $\boldsymbol{X}$ and assign them to form k clusters. Since each cluster has a single element, we denote the initial mean vector of the clusters as $\boldsymbol{m}_1^{(0)}, \cdots, \boldsymbol{m}_k^{(0)}$. The algorithm then proceeds with the following three steps.

1. Assignment Step: All points $\boldsymbol{x}_i$ in $\boldsymbol{X}$ are assigned to $S_j \in \boldsymbol{S}$ via

$$j = \arg\min_u d(\boldsymbol{x}_i, \boldsymbol{m}_u^{(0)})$$

   where d denotes the Euclidean distance. If there are several j satisfying the condition, one randomly assigns the point to one of those S_j.
2. Updating Step: when all points in $\boldsymbol{X}$ are assigned, update the mean vector of each cluster, namely

$$\boldsymbol{m}_j^{(1)} = \frac{1}{|S_j|} \sum_{\boldsymbol{x}_i \in S_j} \boldsymbol{x}_i,$$

   where $|S_j|$ denotes the number of points in S_j.
3. Repeat the Assignment and Updating Steps to obtain $\boldsymbol{m}_j^{(2)}$ and check the condition

$$d(\boldsymbol{m}_j^{(2)}, \boldsymbol{m}_j^{(1)}) = 0, \quad j = 1, \ldots, k.$$

   If the condition fails, repeat Step 3 until it is satisfied.

It is easy to see that the algorithm aims at achieving the stability of the mean vectors. With the stable mean vectors, the clustering is stable too. In theory, the prior algorithm achieves local convergence as the result may depend on the initial assignment. However, one can use different initial assignments to ensure global convergence. In application, some time series may contain outliers that can weaken the accuracy in prediction, leading to inferior clustering analysis. In this case, some data processing might be helpful. For instance, one can apply wavelet smoothing to the observed time series before the modeling. See Nason (2008) for applications of wavelet methods in statistics.

7.3 Empirical Analysis

In this section, we apply the proposed method to a collection of 294 CDS series with 3-year maturity from Markit. The data are from January 2004 to September 2014. A few time series did not start in January 2004. In this case, a shorter time span is

Table 7.1 ARIMA+GARCH Order Combinations

ARIMA order	GARCH order			
	(0,0)	(1,1)	(2,1)	(2,2)
(0,1,0)	0	0	1	9
(0,1,1)	0	0	1	16
(0,1,2)	1	0	0	9
(1,1,1)	4	0	1	21
(1,1,2)	1	0	0	21
(2,1,2)	2	0	0	26
(3,1,2)	0	0	1	10
(3,1,3)	1	0	0	9
(4,1,4)	0	0	3	9
(4,1,5)	0	12	2	5
(5,1,5)	1	18	1	10

used. Since the observed spreads are small, we analyze $y_t = \log(10000s_t)$, where s_t is the observed spreads.

7.3.1 *Modeling and Forecasting*

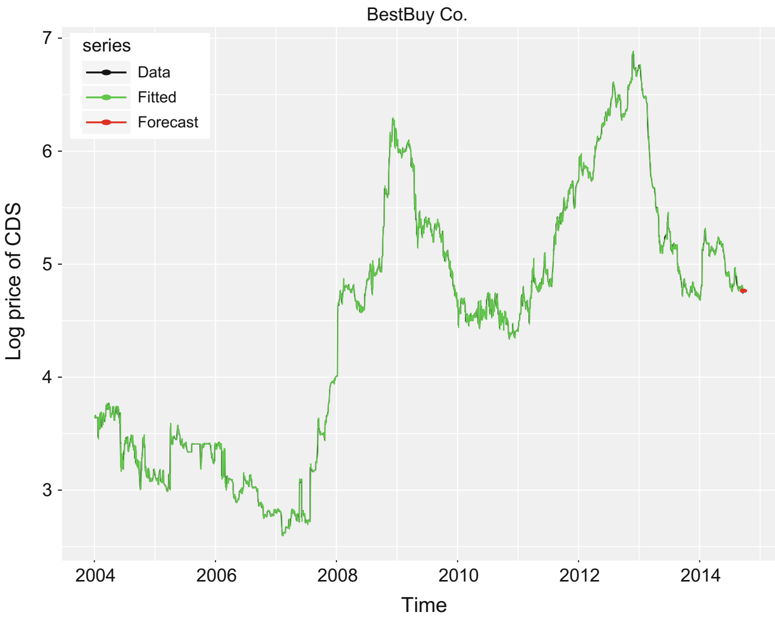
Following the proposed method, we start the analysis with ARIMA-GARCH modeling. Table 7.1 summarizes the main results of ARIMA-GARCH order selection. The ARIMA orders are shown in row whereas GARCH orders in column. These results are selected by AIC with maximum value 5 for both p and q.

From Table 7.1, a majority of the firms assume the GARCH(2,2) structure. On the other hand, the ARMA orders vary markedly. The need for the first difference in the CDS spreads is not surprising as it is in agreement with most time series of asset prices.

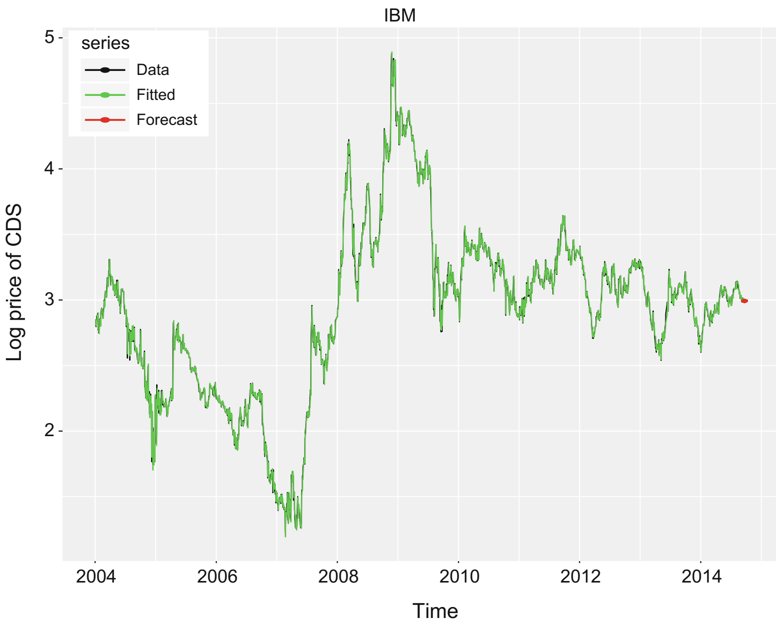
To demonstrate, Fig. 7.1 shows the time plots of observed data, fitted values and 1-step ahead prediction for the 3-year CDS spreads of BestBuy and IBM. The black line, green line, and red point are the observed data, fitted values, and prediction, respectively. From the plots, the fitted models appear to provide good fits.

The plots in Fig. 7.1 also show marked market impacts and difference between companies. Both BestBuy and IBM spreads exhibit substantial increases in default risk during the 2008 financial crisis. On the other hand, the BestBuy spreads show that the company did not do well in 2013. For the IBM series, there was no clear increase in default risk after 2011.

Figure 7.2 shows the time plots of log returns of IBM CDS spreads after wavelet transformation and the associated fitted values. As expected, the model selected by AIC fits the wavelet transformed data well. The main discrepancies between the data



(a) BestBuy



(b) IBM

Fig. 7.1 Observed data, fitted values, and a prediction of 3-year CDS spreads of Best Buy and IBM from January 2004 to September 2014. The data are $\log(10000 s_t)$ for the observed spread s_t

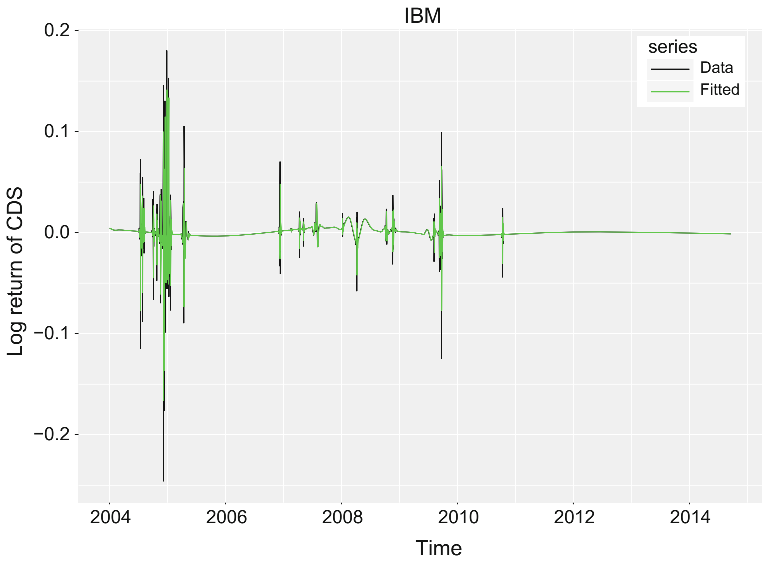


Fig. 7.2 The log return of IBM 3-year CDS spreads after wavelet transformation (in *black*) and the fitted values (in *green*)

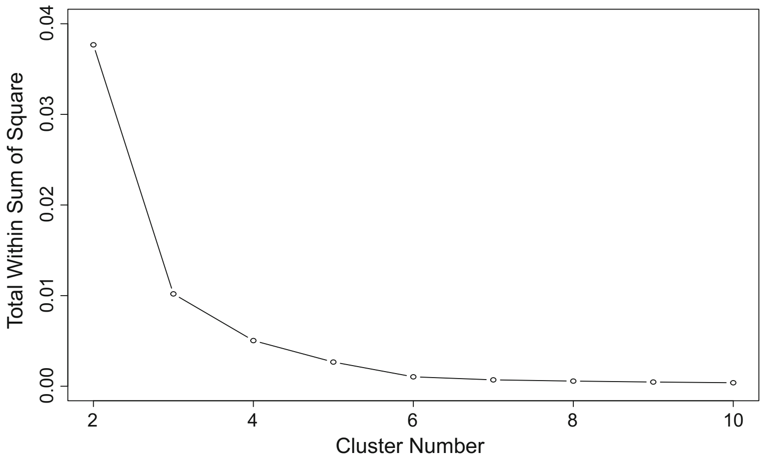
and the fitted value occur during the 2008 financial crisis. The model fits the data well, especially after 2011. This plot indicates that the rating results of the proposed method should be robust to the 2008 financial crisis, because we use 1-step ahead predictions with forecast origin at the end of 2014.

7.3.2 *Cluster Analysis*

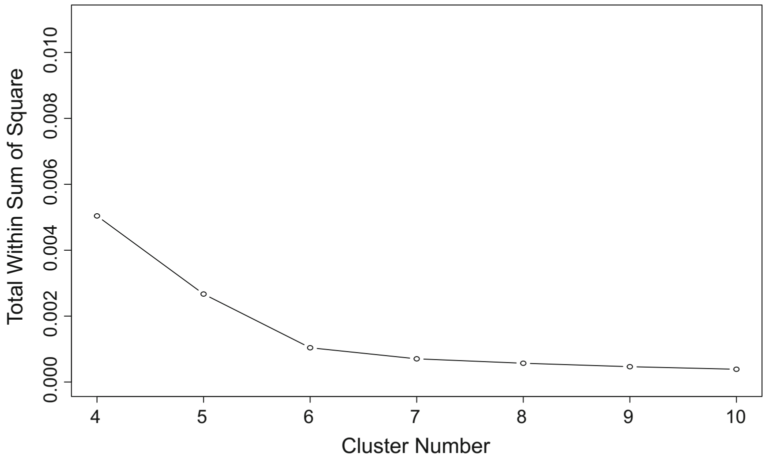
Using 1-step ahead predictions of CDS spreads and their volatilities, we apply the K-means method of classification. Figure 7.3 plots the total within cluster sum of squares versus the number of clusters k. The upper figure shows the results for k from 2 to 10 whereas the lower panel provides a zoom-in view. From the plots, the number of clusters k should be around 6 or 7.

Since there is a bankrupted firm (RadioShack) in the data, we choose the number of clusters to be 8. This would allow Radioshack to form its own cluster. With $k = 8$, Table 7.2 summarizes the results of K-means clustering method. To ensure convergence of the K-means method, the results shown are based on 10,000 initial random starts.

From Table 7.2, most of the firms in our data are clustered into Cluster 1, which has lower values in mean and volatility. Thus, as expected, most firms have low default risk. Assuming that the loss recovery rate is 40 %, the expected implied



(a) The number of clusters ranges from 2 to 10.



(b) Zoom-in Figure

Fig. 7.3 Total within cluster sum of squares (against the number of clusters)

probability of default (IPD) of the best group is $\frac{0.002545244}{1-0.4} \times 3 \times 100\% = 1.27\%$, which appears to be reasonable. This is understandable because the U.S. economy has largely recovered from the 2008 financial crisis. The default risk of a good company should be low. The outlying firm belongs to the worst cluster with spread being ten or hundred times larger than that of other clusters. Such high spread leads to IPD about 100%, confirming that the firm (RadioShack) is indeed bankrupted. Other firms showing relatively high CDS spreads include Toy“R”US (1630bps) and SHC-Acceptance (1715bps). These firms have been known to be in financial stress in recent years, and they are clustered into the categories 5th to 8th. Note that the

Table 7.2 Results of K-mean clustering method, where μ and σ denote the mean spread and volatility of each cluster

Cluster	μ	σ	Size
1	25.45244	0.8541984	196
2	81.26927	2.8876315	51
3	142.66127	5.5291877	32
4	256.70490	28.0481097	5
5	412.27850	7.8975128	5
6	841.41321	102.7335156	2
7	1622.83575	41.0780870	2
8	13910.92850	147.6544963	1

Table 7.3 S&P rating versus the proposed market-based credit rating

S&P Rating	Market-Based Rating Rank				
	1	2	3	4	5
AA+	1	0	0	0	0
AA	1	0	0	0	0
AA-	5	0	0	0	0
A+	4	0	0	0	0
A	20	0	0	0	0
A-	19	1	0	1	1
BBB+	23	2	1	0	0
BBB	27	4	1	0	0
BBB-	10	6	0	0	0
BB+	2	7	2	0	0
BB	1	2	4	1	0
B+	0	1	0	0	0
B	0	1	2	1	1
B-	0	0	1	0	0
CCC+	0	0	0	0	1

estimated IPD and the distribution of firms across clusters match well with the rating results by ICAP (2013) although they used a different data set.

We also compare results of the proposed rating method with the well-known S&P credit ratings. With a limited subsample of 154 firms whose S&P ratings are gathered, results of the proposed clustering method are directional in line with the S&P ratings. See Table 7.3.

Each cell in Table 7.3 shows the number of firms with S&P rating in row and the clustering result in column. Although the proposed method does not differentiate much between good firms, which might be due to the small number of firms available for the comparison, it is reassuring to see that firms with high ratings by the proposed market-based credit rating procedure also have high S&P ratings.

Finally, Fig. 7.4 shows the time plots of median spreads and volatilities for each cluster obtained by the proposed market-based credit rating method. From the plots, the differences between clusters are clearly seen, indicating that the proposed rating method is capable of ranking firms based on their CDS spreads. For instance, Clusters 1 and 2 have lower spreads and volatilities. The defaulted firm had increasing spreads and volatilities over the data span.

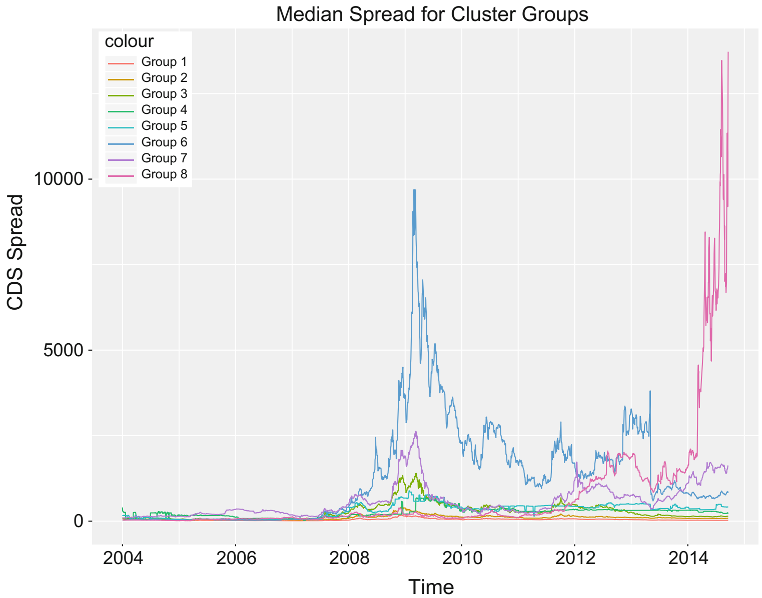
7.3.3 Discussion

Some discussions of the proposed market-based credit rating method are in order. First, as demonstrated by a small subsample, the proposed rating method can produce ratings that are directional in line with those of the S&P rating. This is encouraging as the proposed method only uses the CDS spreads. Indeed, the results show that there exists a close relationship between CDS spreads and the S&P ratings. To demonstrate, we apply a tree-based classification procedure to the S&P rating using the one-step ahead predictions of CDS spreads, indicators of the industrial sectors, and log returns of the spreads as explanatory variables. In other words, we used the subsample of 154 firms mentioned in previous section to build a classification tree with CDS spreads and some additional variables. In a classification tree, branches are determined by relevant explanatory variables with more important variables appearing first and more often.

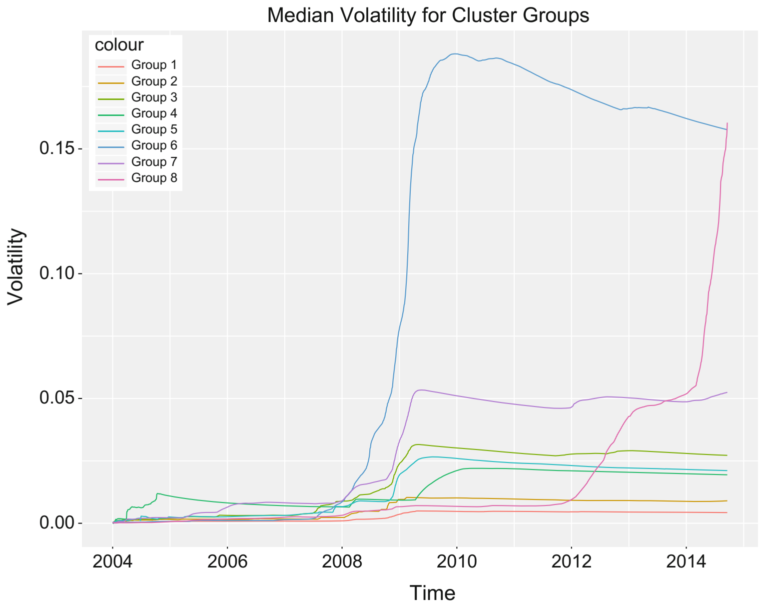
For detailed explanation of tree procedures and pruned tree classification, see James et al. (2013). The resulting tree is shown in Fig. 7.5a. The first few branches of the tree are obtained by either the spread or the standard error of the spreads. The industrial sector only appears in the high-level branches. In the plot, we use alphabets to represent sectors so that the tree is easier to read. Part (b) of Fig. 7.5 shows a pruned tree which provides a clear relationship between the CDS spreads and the S&P ratings. Consequently, CDS spreads are indeed informative about credit risk of a firm.

Second, there are ways to improve the proposed model-based credit rating. For example, a potential weakness of using CDS spreads alone to perform credit rating is that the method might overlook the variations between industrial sectors. Similar to stock returns, the level and volatility of CDS spreads might depend on the industrial sectors. For instance, healthcare companies tend to have lower volatility as their demands are more robust to the U.S. business cycles. Table 7.4 provides the median end-of-year spreads from 2011 to 2013 and the 1-step ahead predictions of 10 industrial sectors to which the 294 time series belong.

From Table 7.4, we see that sectors whose demands are relatively inelastic like healthcare or industrial sectors have lower spreads all year round while the high-elastic demand sectors, including financial and consumer goods, have higher spreads. This is easy to understand because people will lower consumption or investment



(a) Median spreads of each cluster



(b) Median volatility of each cluster

Fig. 7.4 Time plots of the median spreads and volatility for each cluster based on results of the proposed market-based credit rating

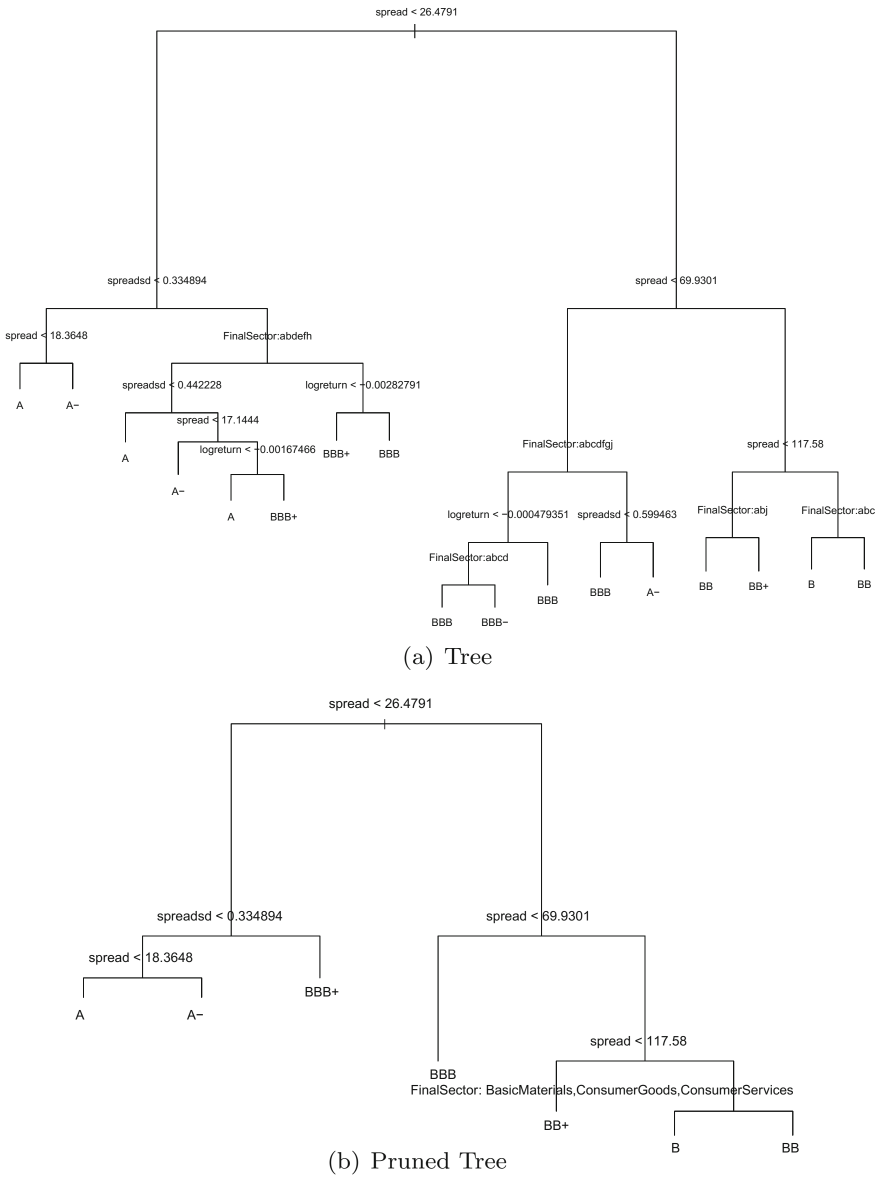


Fig. 7.5 Classification tree on S&P rating

Table 7.4 Median end-of-year CDS spreads from 2011 to 2014 for different industrial sectors

Sector	2011	2012	2013	2014
Basic material	101.32170	66.50631	50.92944	38.05819
Consumer goods	107.78704	68.26233	44.79193	39.74378
Consumer services	109.7089	95.46819	52.94550	39.21939
Energy	70.60976	46.93080	35.96803	33.08610
Financials	164.23591	68.44491	41.62527	32.40109
Healthcare	54.72795	37.95143	21.49869	19.71443
Industrials	64.43414	36.37636	23.81710	23.83260
Technology	103.52434	110.35931	54.64625	41.88988
Telecommunications services	42.88189	42.26581	35.86557	37.04494
Utilities	106.76204	59.46691	34.12895	25.43286

during recession, but will not stop using daily tools or visiting doctors. With the difference between sectors, it seems sector may affect credit rating. However, data from more firms and more sectors are needed to better study the role played by sectors.

Another interesting issue is that volatilities of CDS spreads may vary from sector to sector. Sectors with higher volatilities may be more likely to have lower rating. Since sample variances are sensitive to outliers, we apply wavelet transform to the log returns of CDS spreads. Figure 7.6 shows the scatter plot of sample means and standard deviations of the smoothed log returns for various sectors. The plot confirms that some sectors indeed have higher volatility. Thus, industrial sectors could be used to enhance credit rating. This issue deserves a careful investigation.

7.4 Concluding Remarks

Similar to stock and future prices, CDS spreads reflect the expectation of market participants on credit risk of a firm. Thus, CDS spreads are informative for credit rating. In this chapter, we proposed a market-based credit rating method based on ARIMA-GARCH modeling and prediction of CDS spreads. The proposed method is simple and widely applicable. Limited empirical analysis showed that ratings obtained by the proposed method perform reasonably well. However, further study is needed to improve the results of the proposed rating method. For example, the issue mentioned in the comparison of the proposed method with S&P rating in Sect. 7.3.2 may be solved using additional information. In particular, information concerning industrial sectors, macro-economic factors, and firm size could be helpful.

In the literature, Feng et al. (2008) and Amato and Furfine (2004) argue that there is some effect of business cycle on credit ratings. It's true that macroeconomic factors

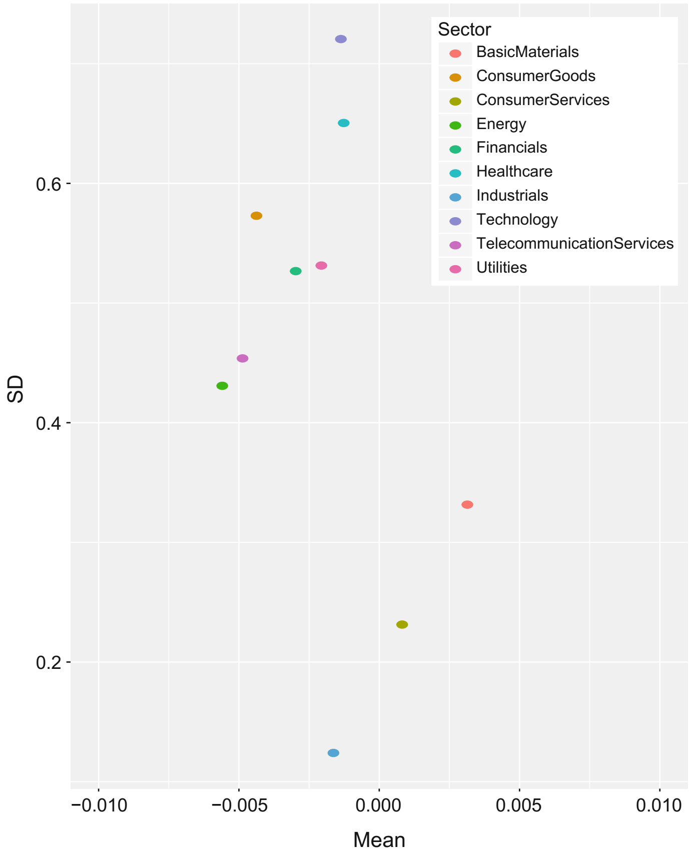


Fig. 7.6 Mean and standard deviation of log returns of CDS spreads across sectors

may affect systematic risk which in turn affect credit ratings. Yet business cycle is still not fully understood or not widely accepted, see Summers (1998). One of such examples is the famous equity premium puzzle in the standard RBC model. Finally, Blume et al. (1998) and Bhojraj and Sengupta (2003) both mention the relationship between credit rating and firm size; thus firm size may be useful in improving credit rating. Intuitively, large firm is less likely to default, or even too big to fail. The issue of firm size also deserves a careful study.

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