FINANCIAL DETERMINANTS OF CORPORATE CREDIT RATINGS IN INDIA

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Credit rating agencies help in bridging the information gap between investors and issuers. The rating agencies provide an opinion on the creditworthiness of the debt instruments. They use qualitative and quantitative information to assign ratings-some of which is not easily available in public domain. Apart from this, there is an element of subjective judgment of the team of experts who arrive at a rating. This makes it very difficult to understand the ratings and the measures used by the rating agencies. A number of research studies have attempted to study credit ratings with the help of publicly available information. In Indian context, most of the studies evaluate the performance of rating agencies in terms of their usefulness to individual and institutional investors. The present paper attempts to empirically analyze the relationship of financial characteristics and credit ratings. Multinomial logistic regression model has been used on a sample of 245 companies in three industries of the manufacturing sector of India- Textile, Steel and Paper. The model depicts a significant relationship between the credit ratings and the selected variables. The independent variables that have been found to be significant determiners of credit ratings are Interest coverage ratio, leverage ratio, profitability ratio and size. The model is able to classify ratings with reasonable accuracy.

Key words: Credit Ratings, Financial Ratios, Multinomial Logistic Regression

INTRODUCTION

The financial markets play the role of an intermediate in a market economy. They arbitrate between an investor in search of investment avenues and the issuer in search of credit. The efficiency of the financial markets depends on the availability of reliable data. There are various sources of information like offer document of the issuer(s), research reports of market intermediaries and media reports. Nevertheless, it is the assessment of the credit rating agencies in the form of credit ratings that is utilized as a tool for risk assessment by the investors.

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According to Standard and Poor's Rating Services[3], a credit rating is a symbolic indicator of the current view of the relative capacity of the issuer to service its debt obligation in a timely manner, with specific reference to the instrument being rated. It is a qualified assessment and formal evaluation of company's credit history and capability of repaying obligations.

The Credit Rating Agencies not only specialize in accumulating information, they also have an access to non-public information. Therefore, they are able to provide independent assessments of the probability of default by companies, governments and the providers of a wide range of financial instruments. Even if they merely collate existing data, they offer service in summarizing the existing disjointed information, and giving an assessment. Thus, the credit rating agencies provide vital information for investors and regulators on one hand and ease the access of funds for the issuer on the other.

There are four international credit rating agencies: Moody's Investors Service, Inc., Fitch, Inc. Standard and Poor's and Duff and Phelps. In India, the ratings industry has been built up to its present position over a period of twenty five years. The ratings have been operating in India since 1988. There are five credit rating agencies recognized by Securities and Exchange Board of India (SEBI). CRISIL (Credit Rating and Information Services of India Limited), ICRA (Investment Information and Credit Rating Agency of India Limited) and Fitch India have collaborative arrangements with S&P, Moody's and Fitch respectively. CARE (Credit Analysis & Research Ltd.) is promoted by IDBI & Canara Bank. Brickworks, the latest entrant, was established in 2008. The Indian credit rating industry is next to United States of America in terms of number of ratings issued.

The growing importance of the credit rating system all over the world is due to many factors such as an increasing role of capital and money markets, increased securitization of borrowing and lending consequent to disintermediation, globalization of the credit market, continuing growth of information technology, growth of confidence in the efficiency of the market mechanism, etc. However, the credit rating agencies are currently facing a reputational crisis. This has been due to their inability to predict the 1997–1998 Asian crises, 2007-09 subprime crisis and the bankruptcies of Enron, World Com and Parmalat. The ongoing sovereign debt crisis in the Euro zone has further raised apprehensions about the credibility of credit rating agencies and is prompting legislators

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[3] Credit ratings http://www.standardandpoors.com/ratings retrieved on September13,2013

worldwide to regulate rating agencies. It is crucial that the credit rating agencies maintain their reputation as reliable and objective source of information. There has been a lot of discussion about the reliability and relevance of the information provided by credit ratings. Closer to home, big corporate giants like Satyam and non banking finance companies floated by C R Bansali (CRB scam) with favorable credit ratings and audit reports collapsed causing losses to many small investors. The accuracy and timeliness of ratings have been debatable.

The credit rating agencies claim that they use qualitative and quantitative information to assign ratings-some of which is not easily available in public domain. Apart from this, there is an element of subjective judgment of the team of experts who arrive at a rating. This makes it very difficult to understand the ratings and the measures used by the rating agencies. The present research work is an attempt to understand credit ratings with the help of financial determinants.

The rest of this paper is organized as follows: The next section discusses the related literature. Section 3 elaborates upon the research methodology of the study. It briefly discusses the variables and method of investigation used in the study. The analysis and interpretation of results is presented in Section 4. The last section presents the conclusion and policy implications.

REVIEW OF EMPIRICAL STUDIES

The econometric methods for analyzing categorical dependent variables have evolved over a period of time. The statistical techniques include multiple regression analysis (Horrigan, 1966; Pogue and Soldofsky, 1969; West, 1970), multiple discriminant analysis (Pinches and Mingo,1973, 1975), ordered linear probit model (OLPM)(Kaplan and Urwitz,1979; Blume et al,1998; Poon,2003;Amato and Furfine,2004; Roje,2005; Gray et al, 2006; Hwang et al.,2008; Purda,2008; Tanthanongsakkun and Treepongkaruna,2008). There are few which have used machine learning techniques, for example, Artificial neural networks (Kumar and Haynes, 2004).

The earlier studies (Horrigan, 1966; Pogue and Soldofsky, 1969; West, 1970) treated the dependent variable i.e. credit ratings as a continuous variable. This was criticized in subsequent studies. The multiple discriminant analysis technique was the most commonly used in earlier studies (Pinches and Mingo, 1973, 1975) to predict credit ratings. The main drawback of the technique was that it does not consider the ordinal nature of bond ratings. It assumes that they are measured on a nominal scale and also that independent variables follow a multivariate normal distribution which is not the case (Kaplan and Urwitz, 1979). However, studies using MDA as prediction technique have been able to predict ratings for approximately 70% of the bonds considered correctly.

The later studies (Kaplan and Urwitz, 1979; Blume et al, 1998; Poon, 2002; Amato and Fur fine, 2004; Roje, 2005; Gray et al, 2006; Hwang et al, 2008; Purda, 2008; Tanthanongsakkun and Treepongkaruna, 2008) used ordered probit model. This is found to have theoretical advantage of treating credit ratings as ordinal discrete variables.

All studies pointed out that credit rating agencies use both quantitative and qualitative information to arrive at credit ratings. It has been seen that earlier studies have been able to develop models that could predict 60 to 75% of the actual bond ratings. A higher percentage of correct predictions has not been possible because of the subjectivity involved in the rating process. The sample size varied from as small as 30 ratings (Rushinek and Rushinek, 1987) to as large as 7324 ratings (Blume et al, 1998). The size of a sample is important especially if the results are to be generalized. Both ordinal logistic and ordinal probit, using maximum likelihood estimates, require a larger sample than ordinary least squares method.

Most of these studies have been conducted in the US market, Australia, China and Nordic countries. With reference to India, most of the studies evaluate the performance of rating agencies in terms of their usefulness to individual and institutional investors in India. The research work by Raghunathan and Verma (1992) and a report (2009) by National Institute of Security Management, Mumbai focus on this aspect. A Report on Comprehensive Regulation for Credit rating agencies(2009) and Ohta H. (2010) focus on how regulatory framework can be made more comprehensive for a more effective and efficient operation of Credit rating agencies in India. The present research work attempts to study the relationship between some financial variables and credit ratings in Indian manufacturing sector.

RESEARCH METHODOLOGY

This section describes the dependent and the independent variables. This is followed by the discussion on statistical and econometric model used in the study.

3(A) Dependent Variable

The dependent variable (Y) is the long term rating of a company assigned by credit rating agencies in India as on July 1, 2012. The long term ratings for the selected companies were obtained from Centre for Monitoring Indian Economy (CMIE)[4] database. The long term credit ratings are issued in alphabetic form and are categorized in six investment grades and four non-investment grades. They further classify companies into subcategories by attaching a suffix '-'or '+' to indicate the relative position of the issuer within the same category. The ratings have been converted to a numerical score for the purpose of statistical analysis. The present study focuses on broad categories. Therefore, positive or negative signs suffixed to ratings are ignored while assigning numerical values. As there were a few observations in the highest categories (AA, AAA) and the lowest categories (D, C), they were merged with the nearest category. Therefore, the present study considers 6 categories of credit ratings ranging from 1 to 6, where 1 denotes the lowest rating and 6 denotes the highest rating. The lowest value is assigned to the lowest rating (highest credit risk).The categorization of the credit ratings into numeric classes, in ascending order, is presented as follows:

$$Y_i = \begin{cases} 1 \text{ if rating} = \text{D, C} \\ 2 \text{ if rating} = \text{B} \\ 3 \text{ if rating} = \text{BB} \\ 4 \text{ if rating} = \text{BBB} \\ 5 \text{ if rating} = \text{A} \\ 6 \text{ if rating} = \text{AA, AAA} \end{cases}$$

The dependent variable (Y_i) includes the ratings assigned to all bonds, non convertible debentures, and other debt instruments (excluding public deposits) with original maturity exceeding one year.

3(B) Independent Variables

There are several studies (Gray, 2003, Hwang, 2009) that have empirically proved the relevance of accounting and financial variables in the determination of credit ratings.

[4] It is considered India's largest and most reliable database on the financial performance of Indian companies. It was established in 1976 and is a leading business information company.

The present study includes only those financial indicators that have been used either in explaining credit ratings in the extant literature or they are considered relevant by the rating agencies. The majority of these indicators are in the form of ratios. The use of financial ratios facilitates the comparison of financial indicators of companies of different size. Ratios are helpful in defining broadly a company's position relative to rating categories.

In the following paragraphs, the definition, measure and the relevance of the selected financial ratios and size in the context of credit ratings have been discussed:

a. *Interest Coverage Ratios* measure the company's ability to service principal and interest payments. A high interest coverage ratio translates into high credit ratings. The measure of the interest coverage that has been found to be significantly associated is the ratio of earnings before interest, tax, depreciation & amortization to interest. The following ratio has been used for further analysis.

Interest Coverage Ratio =EBITDA/Interest

The empirical hypothesis that is tested in the present study is that interest coverage ratio is directly related to the credit ratings.

b. *Leverage ratios* indicate the financing structure of a company. Higher the leverage, smaller is the cushion for adverse events. The measure of the leverage that has been found to be significantly associated with credit ratings is the ratio of debt to equity. The following ratio has been used for further analysis.

Leverage ratio = Debt/Equity

Debt includes short term as well as long term debt and Equity is measured by the total market value of preference and equity shares. The empirical hypothesis that is tested in the present study is that leverage ratio is inversely related to the credit ratings.

c. *Profitability ratios* measure the performance of a company in terms of its ability to generate earnings to cover expenses in a particular period. Higher profitability translates into higher equity value and credit ratings of a firm. There are three measures of the profitability ratios that have been found to be significantly associated with credit ratings. The following ratios have been used for further analysis.

Profitability ratio(1) =PBITDA/Sales

Profitability ratio(2) =PBIT/Average Total Assets

Profitability ratio(3) =Std deviation of earnings/Total assets

These three ratios provide useful insights into financial health and performance of the company. While PBITDA to Sales ratio is an indicator of operating performance, PBIT to Average Total Assets is an indicator of how efficiently a company manages its assets to earn its profits. The earning variability ratio indicates the extent of stability a company has with respect to its profits and a high earning variability ratio is an indicator of bad financial health. The empirical hypothesis that is tested in the present study is that PBITDA/Sales and PBIT/Average Total Assets ratios are directly related to the credit ratings. However, earning variability is inversely related to the credit ratings.

d. *Liquidity ratios* help to assess the company's ability to convert its current assets into cash to cover its debts. A comfortable liquidity ratio is viewed favorably by the rating agencies. The measure of liquidity that has been found to be significantly associated with credit ratings is the cash ratio. The following ratio has been used for further analysis.

Liquidity ratio= (Cash + Marketable securities)/current liabilities

The empirical hypothesis that is tested in the present study is that liquidity ratio is directly related to the credit ratings.

e. *Turnover ratios* reflect the efficiency with which a company's management employs its assets. The turnover ratios have not been found to be significantly associated with credit ratings; therefore, they have been excluded from the final analysis.

f. *Size* is an important consideration as larger companies have advantages in terms access to managerial expertise, economies of scale and a diversified product portfolio. All these attributes translate into a stronger competitive position. The size of a company is measured by the average of total assets of the company.

Size=Average Total Assets

The empirical hypothesis that is tested in the present study is that size is directly related to the credit ratings.

3(C) Multinomial logistic regression[5]

This technique has been used to investigate the impact of the explanatory variables on the credit ratings. The credit ratings, Y, of a company i, (Yi) have been studied as a function of the explanatory variables in the following model:

Credit Ratings (Yi)= f (financial characteristics, size and industry)

Logistic regression models the probability of one of the two outcomes using the independent variables. The logistic regression equation is as follows: Logistic regression models the probability of one of the two outcomes using the independent variables. The logistic regression equation is as follows:

$$Log(Prob(Y_i^*) / Prob(Y_k^*) = \alpha_i + \beta_j X_j$$

Where $Log(Prob(Y_i^*) / Prob(Y_k^*)$ is the log of odds of i outcomes with respect to a referent outcome k (i varies from 1 to k-1.).

This can be presented as follows:

$$\log \frac{Pr(Y_i^* = 1)}{Pr(Y_i^* = k)} = \alpha_i + X_j \beta_{1j}$$

$$\log \frac{Pr(Y_i^* = 2)}{Pr(Y_i^* = k)} = \alpha_2 + X_j \beta_{2j}$$

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$$\log \frac{Pr(Y_i^* = k-1)}{Pr(Y_i^* = k)} = \alpha_{k-1} + X_j \beta_{k-1j}$$

The probabilities of each category can be found by exponentiating the log of odds ($Exp(\alpha_i + \beta_j X_j)$) as shown below:

$$Pr[Y_i^* = 1] = \frac{\exp^{\alpha i + Xj\beta 1j}}{1 + \sum_{i=1}^{k-1} \exp^{\alpha i + Xj\beta ij}}$$

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[5] Flom P.L. (n.d.) National Development and Research Institutes, Inc. Multinomial and ordinal logistic regression using PROC LOGISTIC. Retrieved on May 7,2013 from http://www.nesug.org/proceedings/nesug05/an/an2.pdf

$$\Pr[Y_i^* = 2] = \frac{\exp^{\alpha i + Xj\beta 2j}}{1+\sum_{i=1}^{k-1} \exp^{\alpha i + Xj\beta ij}}$$

....

$$\Pr[Y_i^* = k-1] = \frac{\exp^{\alpha i + Xj\beta (k-1)j}}{1+\sum_{i=1}^{k-1} \exp^{\alpha i + Xj\beta ij}}$$

Multinomial logistic regression is an extension of the binary logistic regression. It generalizes logistic regression by allowing more than two outcomes of dependent variables which may be non-metric: nominal or ordinal. The independent variable may be metric or non metric. It describes polytomous responses by a sequence of binary models. If the ordinal dependent variable is divided into k categories, it compares the probability of being in each of the (k-1) categories compared to a reference category k.

ANALYSIS AND INTERPRETATION OF RESULTS

The preliminary investigations included correlation statistics, descriptive statistics and measures of association (Table 4, 5 and 6 in endnotes). The correlated variables are identified using correlation matrix and variance inflation factor. Thereafter, measures of association are used to select the financial variables for the final model. The financial variables selected for the final models included one interest coverage ratio, one leverage ratio, three profitability ratios, a liquidity ratio , a size and industry variable. The variables are transformed since they are highly skewed, possessed a high range and variance using data transformation techniques. The data is also checked for outliers and influential cases. As a result of this, six cases are excluded from the final sample.

A frequency distribution of ratings assigned to the companies in the sample is as follows:

Table 1 Frequency distribution of ratings assigned in the given sample

Ratings code	Ratings	Frequency	Percent
1	D,C	36	14.7%
2	B	21	8.6%
3	BB	64	26.1%
4	BBB	72	29.4%
5	A	36	14.7%
6	AA,AAA	16	6.5%
		245	100%

Source: On the basis of SPSS output

As can be seen from the above table, 50.6% of the ratings are in the investment grade (BBB and above) and 49.4% are in the speculative grade.

The main objectives of the research are to find out the determinants of credit ratings and empirically investigate their significance using the multinomial logit regression methodology. The regression analysis examines the nature and direction of relationship between the credit ratings and independent variables with respect to the research hypothesis. Multinomial logistic regression with credit rating as dependent variable and the eight predictors (seven selected explanatory variables discussed above and a dummy variable for industry where textile, paper and steel are coded as 1, 2 and 3 respectively) are examined in the model. Multinomial logistic regression is an extension of the (binary) logistic regression and has been presented in the following equation:

$$Y_i^* = \log \frac{\Pr(Y=j)}{\Pr(Y=k)} = \alpha_i + \beta_j X_j$$

The left hand side gives the log of odds of being in a category as compared to the referent category. In the given equation, j= categories (1, 2....6) of credit rating, Y and k is the referent category. The exponent of the log of odds (Exp (β)) is taken to interpret in terms of odds ratio (a ratio of an outcome to the other). It indicates how different predictors affect the likelihood of being in each category versus the referent category. The results of the model have been discussed and interpreted in the following paragraphs:

Table 2: Likelihood Ratio Test and Pseudo R-Square results

Explanatory Variables	-2log likelihood	p-value
EBITDA/Interest	541.133	.002
Debt /Equity	551.147	.000
PBITDA/Sales	524.787	.562
PBIT/Average Total Assets	525.581	.001
Std deviation of earnings/Total assets	542.297	.740
Cash ratio	524.412	.682
Average Total Assets	627.199	.000
Industry	537.144	.116
Overall model fit		.000
Pseudo R-square		.72

On the basis of likelihood ratio test, the model with the eight explanatory variables depicts significant relationship between the credit ratings and the selected predictors. The Nagelkerke R^2 is 72% which implies that the selected variables explain approximately 72% of the variation in the outcome variable i.e. credit ratings. The four independent variables that have been found to be significant determiners of credit ratings are interest coverage ratio, leverage ratio, profitability ratio and size. The results indicate that rating agencies place more importance on the ability of the issuer to judiciously use its capital employed (Return on Assets) rather than other aspects of profitability like operating performance or earning variability. On examining the mean values of operating performance (PBITDA/Sales) and earning variability (Std deviation of earnings/Total assets) across all the categories (Table 6, Endnotes) a clear monotonic relationship (on expected lines) between these two variables and credit ratings is observed. This indicates that these factors are relevant but do not significantly influence the rating decisions. The findings reveal that liquidity is not significantly related to credit ratings. This substantiates the empirical evidence (Gopalan et al, 2009) that rating agencies tend to underestimate the liquidity risk. The results also do not find industry to be a significant variable. This is because all the three industries belong to the manufacturing sector and rating agencies investigate common set of ratios.

Classification Results

The findings support the hypothesis that the model with interest coverage, financial leverage, profitability, operating performance, earning variability, liquidity, size and industry as independent variables for determining credit ratings is valid. The accuracy of the multinomial logit regression model in predicting the credit ratings with the help of the selected financial variables can be found by cross tabulation of observed credit ratings and predicted credit ratings. The classification results have been presented in the following table:

Table 3: Classification table

Observed	Ratings classified by the model					
	C,D	B	BB	BBB	A	AA,AAA	%Correct
C,D	22	1	6	6	1	0	61.1%
B	6	2	9	4	0	0	9.5%
BB	3	1	47	12	1	0	73.4%
BBB	2	0	8	55	7	0	76.4%
A	2	0	0	8	25	1	69.4%
AA,AAA	0	0	1	1	4	10	62.5%
	14.3%	1.6%	29.0%	35.1%	15.5%	4.5%	65.7%

Source: On the basis of SPSS output

The proportional by chance accuracy rate is computed by squaring and summing the proportion of cases in each category in the given sample ($0.143^2 + 0.086^2 +$

$0.261^2+.294^2+.147^2+.065^2=.208$) (From Table 1).The proportional by chance accuracy criteria is 26% (1.25 x 20.8% = 26%). The given model is considered useful as it makes correct classifications to the extent of 65.7% with maximum correct classifications (76.4%) made in the fourth category (BBB) followed by third (73.4% in BB) and fifth category (69.4% in A). It is also observed that 23% of ratings missed the perfect classifications by only one category. Therefore, the given model is able to classify with reasonable accuracy.

CONCLUSION

The multinomial logit regression model is applied on a sample of 245 companies. On the basis of likelihood ratio test, the model with the 8 selected explanatory variables depicts significant relationship between the credit ratings and the selected predictors. The Nagelkerke R^2 is 72% which implies that the selected variables explain approximately 72% of the variation in the outcome variable i.e. credit ratings. There are four independent variables found significant determiners of credit ratings –interest coverage ratio, leverage ratio, profitability ratio and size.

The given model is considered useful as it is able to correctly classify 65.7% with maximum correct classifications (76.4%) made in the third category (BBB) followed by second (73.4% in BB) and fourth category (69.4% in A). It is also observed that 23% of the ratings missed the perfect classification by only one category. Therefore, the model is able to classify with reasonable accuracy. Further, it is found that the proportion of correct classifications is similar across the three manufacturing industries (Textile- 66%, Paper -62% and Steel- 64%). This implies that the model with financial variables holds well across the three industries.

The study offers the corporate management a rating yardstick against which they can assess themselves and act as guidelines for the firms in the quest for a rating solicitation. The empirical results with respect to financial characterstics may be used as an apparatus to appraise the financial situation of the business counterparts, suppliers and customers. The research findings have equally important implications for the investors. The information asymmetry is one of the reasons for the lack of development in the corporate bond market in India. An investor has neither the means nor the capability to evaluate the creditworthiness of an issuer. He is completely dependent on the credit rating of the debt instrument for an overall assessment of a company's credibility. This research can provide guidance to the investors to interpret ratings and make the right investment decision. There is a danger in overemphasizing the importance of credit ratings since their ability to predict financial defaults has come under scanner in the wake of recent financial failures. The results depict that it is possible to capture the rating method employed by rating agencies to a large extent if suitable financial variables are included. Therefore, it is possible that a company may time their bond issues when they have impressive financial ratios in the immediate past and obtain a good rating. Thus, there is a need to re-evaluate the role of credit ratings. A credit rating should not be understood as a guideline to investment by investors and institutions with relatively long planning horizons. It is recommended to diversify across all rating groups if the information obtained through models developed in the study indicates sound overall health.

Endnotes

Table 4 Measures of Association for the selected variables

S.no.	Explanatory variable	Description	Somers'd (p-value)	Gamma (p-value)
1.	Interest Coverage	EBITDA/Interest	.418 (.000)	.519 (.000)
2.	Leverage	Debt /Equity	-.301 (.000)	-.375 (.000)
3.	Profitability	PBITDA/Sales	.285 (.000)	.354 (.000)
4.	Profitability	PBIT/Average Total Assets	.367 (.000)	.457 (.000)
5.	Earning Variability	Std deviation of earnings/Total assets	-.329 (.000)	-.391 (.000)
6.	Liquidity	Cash ratio	.172 (.000)	.216 (.000)
7.	Size	Average Total Assets	.279 (.000)	.352 (.000)

Source: On the basis of SPSS output

Table 5: Correlation matrix of the transformed explanatory variables

	Independent variables	2	3	4	5	6	7	8
1.	EBITDA/Interest	1						
2.	Debt /Equity	-.360**	1					
3.	PBITDA/Sales	.293**	-.120	1				
4.	PBIT/Average Total Assets	.464**	-.323**	.604**	1			
5.	Std deviation of earnings/Total	-.277**	.386**	-.333**	-.496**	1		
6.	Cash ratio	.380**	-.214**	.262**	.208**	-.200**	1	
7.	Average Total Assets	.173**	.015	.338**	.118	-.091	.179**	1

***Correlation is significant at the .01 level(2 tailed*

Table 6: Descriptive statistics of the transformed variables

C,D	EBITDA/ Interest	Debt / Equity	PBITDA/ Sales	PBIT/Average Total Assets	Std deviation of earnings/ Total assets	Cash ratio	Size
Mean	2.57	302.49	16.76	13.32	2.27	0.71	3.31
Median	2.58	279	17.24	12.56	2.23	0.68	3.33
Std. Deviation	0.15	159.63	6.52	5.46	0.54	0.34	0.37
Skewness	-0.68	-0.03	-0.24	0.4	1.64	0.33	0.06
Kurtosis	0.69	-1.29	-0.27	0.98	4.47	-0.6	-0.85
Minimum	2.14	0	0.87	0.93	1.45	0.1	2.63
Maximum	2.86	500	28.59	29.2	4.3	1.44	4.05
B							
Mean	2.7	271.51	18.71	15.9	2.2	0.69	3.17
Median	2.66	207.5	18.43	16.31	2.11	0.65	3.17
Std. Deviation	0.17	149.46	4.51	3.65	0.55	0.22	0.53
Skewness	1.58	0.25	-0.16	-0.37	0.68	0.31	-0.18
Kurtosis	3.95	-1.13	-0.84	-0.47	-0.30	1.17	-1.30
Minimum	2.44	22.75	10.29	7.84	1.49	0.18	2.14
Maximum	3.25	500	25.88	21.29	3.39	1.19	3.83
BB							
Mean	2.67	261.99	19.47	17.74	2.09	0.72	3.10
Median	2.66	211.63	18.98	17.69	1.98	0.72	3.13
Std. Deviation	0.08	159.00	4.55	3.48	0.62	0.29	0.47
Skewness	0.50	0.35	0.94	-0.58	0.94	0.44	0.16
Kurtosis	-0.02	-1.27	1.80	2.77	1.23	1.18	0.2
Minimum	2.53	0	8.45	4.1	0.67	0	2.19
Maximum	2.88	500	34.88	25.4	4.04	1.69	4.58

BBB							
Mean	2.79	195.49	21.54	19.35	1.86	0.77	3.45
Median	2.76	185	21.01	18.87	1.77	0.73	3.43
Std. Deviation	0.19	110.54	5.75	3.67	0.49	0.38	0.52
Skewness	2.23	1.09	1.38	0.06	0.90	0.47	0.43
Kurtosis	8.42	1.26	4.17	-0.07	0.48	-0.11	0.49
Minimum	2.47	8.5	11.66	10.36	1.09	0.1	2.44
Maximum	3.75	500	46.61	28.04	3.34	1.82	5.15
A							
Mean	2.86	147.95	25.17	21.72	1.61	0.97	3.95
Median	2.84	141.75	23.23	19.80	1.59	0.91	3.88
Std. Deviation	0.23	87.78	7.88	6.20	0.38	0.40	0.55
Skewness	1.23	0.52	0.56	1.40	0.56	0.55	0.48
Kurtosis	2.72	-0.42	0.74	2.64	-0.25	-0.66	0.56
Minimum	2.37	22	7.21	8.9	0.99	0.35	2.85
Maximum	3.56	351.25	45.87	40.34	2.56	1.82	5.37
AA,AAA							
Mean	3.05	101.05	28.75	23.65	1.60	1.13	4.60
Median	2.98	82.87	28.85	23.12	1.54	1.16	4.62
Std. Deviation	0.34	74.77	8.55	7.24	0.60	0.40	0.75
Skewness	0.62	1.31	0.12	0.14	1.59	-0.06	-1.03
Kurtosis	-0.03	1.38	0.77	-0.31	4.69	-0.7	1.86
Minimum	2.54	6	10.54	10.76	0.68	0.4	2.72
Maximum	3.75	281.75	45.38	37.98	3.36	1.82	5.81

Source: On the basis of SPSS output

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