Empirical Study of Credit Rating Migration in India

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Abstract

Credit rating agencies assess the credit worthiness of specific debt instruments. To determine a bond's rating, a credit rating agency analyzes the accounts of the issuer and the legal agreements attached to it, to produce the chance of default, expected loss or a similar metric. The metrics vary between agencies. The upgrade and downgrade of ratings is known as notching. The probability of single and multiple notching is represented by a matrix of transition probabilities. The matrix is defined to describe the probability for change in an underlying rating. Rating migration refers to a change from an initial rating to a new rating category. Transition matrix represents the probability of a company moving from one credit rating to another i.e. the chance of credit quality of a firm improving or worsening. It represents moving probabilities from one rating level to all other ratings, including default for a given rating and time horizon. It shows the complete possible states that a rating can take over a given time horizon and therefore provides detailed information on rating movements. When credit quality of corporate bonds worsens, the probability of future default also increases. We have estimated transition matrix for companies rated by ICRA using two estimation procedures built on historical transitions - Cohort approach and Hazard approach - using five years' data from Bloomberg between 2012 and 2017.

Keywords: *Credit Risk, Credit Rating, Credit Risk Management, Probability of Default*

Introduction

In order to sustain high growth rates, India needs a developed bond market. In its current state, it is a market for highly rated, plain vanilla instruments, issued by financial firms and Public Sector Enterprises (PSEs). Also, issuance is fragmented and trading dries up within a few days of issuance. The Indian bond market comprises of three segments; government bond market, corporate bond market and the derivatives market. Corporate bond markets can be split into domestic and international. The domestic corporate bond market's size, depth and activity is likely to be influenced by the size of the government bond market, the number of listed companies, bank assets as a percentage of GDP, etc. Another factor that may be relevant in understanding the development of the corporate bond markets in India is the role that credit rating agencies play. This study is related to the domestic corporate bond market in India and this paper intends to study default risk and rating changes to bring about greater understanding of credit risk faced by corporate bonds in India.

The present paper is organised as follows. Section I presents an overview of the corporate bond market in India; Section II presents the role of rating agencies; in Section III, we introduce the idea of transition matrix; Section IV presents the survey of literature; Section V presents the methodology to estimate transition matrices used in this study; Section VI describes the data used in this study; Section VII describes the results and interpretations and Section VIII concludes with policy implications.

The Corporate Bond Market in India

The Indian corporate debt market has experienced considerable growth in recent years. Today, the size of the corporate bonds' market is about Rs.19 trillion — around 14% of the Gross Domestic Product (GDP). This is large on an absolute basis but small compared to bank assets (89% of GDP) and equity markets (80% of GDP). Banks and equity markets are the dominant sources of capital for business in India. Corporate bond market financing in India continues to be dwarfed by bank financing and equity financing. This is a puzzle. Several committees have opined on how to fix this, yet little has changed. As of December 2015, the total volume of outstanding corporate bonds in the Indian bond market amounted to approximately $287bn.

Table 1:
Financial Market Development

As % of GDP	1996	2008	2015
Equities	32.1	108.4	80.0
Government bonds	14.3	36.1	34.3
Corporate bonds	0.9	3.9	14.0
Bank assets	46.5	73.8	89.0
Source: SEBI, RBI, World Economic Outlook			

The corporate debt market can be classified into primary market and secondary market. In the primary market, corporate debt is via private placements like corporate bonds placed with wholesale investors like banks, financial institutions, mutual funds, etc. The secondary market for corporate debt is available on platforms offered by various exchanges in the country.
The following are the instruments available in the corporate debt market - Non-convertible debentures; partly-convertible debentures/ fully-convertible debentures (convertible into equity shares); secured premium notes; debentures with warrants; deep discount bonds; PSU bonds/ tax-free bonds. The participants in the retail debt market can be divided into mutual funds, provident funds, pension funds, private trusts, religious trusts and charitable organizations having large investible corpus, state level and district level co-operative banks, housing finance companies, NBFCs and RNBCs, corporate treasuries, Hindu-Undivided Families (HUFs) and individual investors.

Table 2:
Primary Market for Corporate Bonds

Year	Issuance details		% change in issuance	Net outstanding (As at end-March)	No. of outstanding instruments	% change in outstanding amount
	No. of issues	Amount				
2012-13	3,023	380,411.62	27.48	1,261,717.15	8,859	23.79
2013-14	3,136	383,320.05	0.76	1,466,057.68	9,186	14.61
2014-15	4,257	466,247.13	21.63	1,702,756.47	10,810	17.75
2015-16	4,696	564,099.70	20.99	1,956,445.64	12,624	14.90
Source: SEBI						

Bond markets help diversify the sources of financing and reduce credit risk concentration in the banking sector. A liquid corporate debt market can play a crucial role by supplementing the banking system to meet the requirements in the corporate sector for long-term capital investment and asset creation. In India, various recommendations announced by numerous committees (R H Patil Committee 2005, Percy Mistry Committee 2007, Raghuram Rajan Committee 2009, H R Khan Committee 2016) have resulted in a series of reforms to deepen and develop the corporate bond market. As a result, the corporate bond issuance has increased by 77% between 2010-11 and 2014-15 while the number of issues has jumped 156%. Net outstanding too increased by 97% during the same period. If we extend the period by one more year, bond issuance between 2010-11 and 2015-16 increased 95%, issuance amount by 116% and net outstanding by 127%.

Table 3:
Secondary Market

Year	No. of issues	Value outstanding (Rs. bn)	No. of trades	Traded value (Rs. bn)	Avg. trade size (Rs. bn)	Turnover ratio
2008			19,079	958.9		
2009			22,683	1,481.7		
2010			38,230	4,011.9		
2011	12,155	8,895.1	44,060	6,052.7	0.14	0.68
2012	13,721	10,516.4	51,533	5,937.8	0.12	0.61
2013	15,874	12.901.5	66,383	7,386.3	0.11	0.63
2014	13,104	14,673.9	70,887	9,708.0	0.14	0.70
2015	19,439	17,503.2	75,791	10,912.9	0.15	0.68
Source: SEBI						

In the corporate bond market, funds are raised through either public issues or via private placements. While the private placement disclosure and documentation requirements are viewed by the market to be comprehensive, disclosure requirements for public issuance of debt are viewed by the market as being extremely arduous and difficult to comply with. As an active market for corporate debt does not exist, it does not make any economic sense to spend a good amount in issuance. Hence, this market is dominated by private placements. Out of total corporate debt issuances, high rated bonds considered to be the safest bet have the largest share. AAA and AA rated bonds had a combined share of over 72% in total Corporate Bond issuances over the years.

Table 4:
Modes of Debt Issues Used by Corporate Sector

Year	Debt issues (Rs Crore)				Total
	Public		Private Placement		
	Amt	Share (%)	Amt	Share (%)	
2012-13	16,982	4.49	361,462	95.51	378,444
2013-14	42,383	13.31	276,054	86.69	318,437
2014-15	9,713	2.35	404,137	97.65	413,850
2015-16	33,812	6.87	458,073	93.13	491,885
Source: SEBI					

The turnover ratio is the value of bonds traded in the secondary market to the total outstanding bonds. It is indicative of the liquidity in the bonds market as it captures the extent of trading in the secondary market relative to the amount of bonds outstanding. Hence, higher the turnover ratio, more active is the secondary market. The table below gives an overview of the turnover ratios in government bonds, corporate bonds and aggregate bonds in Asian countries. Japan has the highest turnover ratio of 4.56 with government bonds having a multiple of 4.9. The turnover in the corporate bond market is relatively lower at 0.3. India is second with a healthy turnover in the bond market at 3.46. There is a strong secondary market for government securities with a turnover of 4.7. India's position in terms of turnover is mirrored in the corporate bonds market as well with a turnover ratio of 0.67, which is still higher than that of Japan. China leads in the corporate segment with a multiple of 1.6. In fact, China has a turnover ratio of above 1 in both the segments. Thailand is third with a total turnover of 2.5, with a 3.1 turnover in government bonds and corporate bonds turnover being 0.26. While South Korea has a larger corporate debt market size relative to GSecs, the turnover ratio is higher for gilts at 3.73 compared with 0.54 for corporate bonds. Domestic credit (i.e. credit disbursed by banks) is the primary source for financing in China (73.9%) and South Korea (73.9%) followed by India which is second with a share of 71.5%. In emerging markets, corporate bonds are not significant; India has the highest share with 18.4% followed by Malaysia with 12.4% and China, S Korea and Singapore with 8% each. Interestingly, relative to other countries, India lends the most through corporate bond issuances at 18.4% standing well above its peer countries in the sample. Hence, despite a smaller contribution of corporate bonds in India (in terms of outstanding issuances) relative to other countries, corporate bonds play a larger role in satisfying the finance needs of corporates compared with other countries in the sample.

Table 5:
Global Bond Markets – Market Size

Country	Bond market Size-2015 (as % of GDP)				GDP
	Total	Government	FI	Non-FI	(USD Bn)
USA	207	90	86	30	17,348
China	60	17	23	19	10,357
Japan	243	182	48	14	4,602
UK	201	88	95	18	2,950
India	49	34	10	4	2,051
Korea	103	36	32	35	1,410
Indonesia	13	11	1	1	889
Thailand	81	28	32	21	405
Singapore	108	24	53	31	308
Source: BIS Debt Statistics: IMF World Economic Outlook; ADB Asian Bonds Online					

A critical positive is that the turnover in the Indian bond market is second only to Japan. However, this is primarily owing to the active secondary market for government bonds in the country. The secondary corporate bond market, while being comparatively passive, is still the second most active within Asian countries. Hence, while overall, the secondary market trading appears healthy, the same for corporate bonds can be made more vibrant.

Table 6:
Global Bond Markets - Turnover

	Govt. bonds Outstanding ($ Bn)	Turnover ratio	Corporate bonds Outstanding ($ Bn)	Turnover ratio
USA	15,614	9.7	20,147	1.6
China	1,779	1.3	4,390	0.9
Japan	8,363	5.3	2,839	0.3
UK	2,598	N.A.	3,327	N.A.
India	704	1.9	287	0.7
Korea	505	3.04	944	0.5
Indonesia	101	2.7	19	0.8
Thailand	112	2.6	215	0.3
Singapore	73	1.9	259	N.A.
Source: ADB Asian Bond Online, BIS Debt Statistics, SIFMA, SEBI, RBI				

The above analysis indicates that despite having a large bond market, countries like China and South Korea have a relatively passive secondary market as opposed to India which stands fourth in terms of the size of the bond market, but is second with respect to the turnover in the bond market as a whole and also in the individual government and corporate bond markets.

Role of Rating Agencies

In India, as in other economies, credit ratings are important for private contracting as well as regulation. In carrying out these functions, rating agencies play a key role in reducing asymmetric information which helps in the formation of both primary and secondary markets. Credit rating agencies are companies which specialize in evaluating the creditworthiness of an issuer of debt instruments (bonds, securities etc). The issuer can be a company or a government. Credit rating agencies use simple alphabetical or alphanumeric symbols which help the investor differentiate between debt instruments on the basis of their underlying credit quality. Just like a school report card, these grades serve as a marking system /score card designed to inform interested parties about the creditworthiness of countries, companies and individuals.

A rating agency mainly assigns a rating to a bond. The rating is based on two elements: the probability that the entity will file for bankruptcy before the final bond payment is due and what percentage of the bondholders' claims creditors will receive if a bankruptcy takes place. The upgrade and downgrade of ratings is called Notching. Rating notches can be single notching or multiple notching. The probability of single and multiple notching is captured by a matrix of transition probabilities. The matrix is defined to describe the probability for change in an underlying rating. Thus "rating migrations" refer to a change from an initial rating to a new rating category.

The credit rating indicates the rating agency's opinion on the likelihood of default by the issuer. Credit ratings establish a link between risk and return. It is arrived at by evaluating various quantitative as well as qualitative parameters of the issuer. Lower credit ratings result in higher borrowing costs because the borrower is believed to carry a higher risk of default. In other words, when you invest in an instrument issued by someone with a weak credit score, you are hoping for a higher rate of return.

The rating symbols provided by the agencies indicate both the returns expected and the risk attached to the instrument. Hence, it becomes easier for the investors to base their decision by looking at the symbol assigned by the rating agencies. Credit rating activity began in March 1988 in India with CRISIL assigning a rating to its first client IPCL.

Six agencies are currently recognized and regulated in India: CRISIL Limited, incorporated in 1987; India Ratings & Research (INDRA), incorporated originally as Duff and Phelps Credit Rating India Private Limited in 1996; ICRA Limited, incorporated in 1991; Credit Analysis & Research Ltd. (CARE), incorporated in 1993; Brickwork Ratings India Private Limited, incorporated in 2007; and SME Rating Agency of India Ltd. (SMERA), incorporated in 2005. In terms of revenue, CRISIL is India's largest rating agency, followed by ICRA and CARE.

For all debt market participants, accurate and reliable default and transition rates are critical inputs in formulating the following decisions. First, default and transition rates are critical inputs for pricing a debt instrument or loan exposure; this helps to decide whether and how much to lend and at what price. Second, the structuring, rating and pricing of credit-enhanced instruments depend heavily on the default and transition rates of underlying borrowers and securities. Third, default and transition rates are key inputs for many quantitative risk assessment models. Investors in rated instruments can manage their risk exposures efficiently if they have access to reliable default and transition rates. Transition rates are also important for debt funds that need to maintain a certain threshold of credit quality in their portfolios and for investors who are mandated to invest only in securities that are rated at a certain level or above.

Table 7:
Rating Analysis of the Issuances of Fixed Rate Corporate Bonds

Year	AAA	AA	A	BBB	BB	B	C	NA
2012-13	433	470	117	24	9	0	3	73
2013-14	481	846	125	41	26	7	3	179
2014-15	789	929	241	126	53	5	0	217
2015-16	907	963	204	103	50	8	0	267
Source: NSDL								

Transition Matrix

Credit ratings rank borrowers according to their credit worthiness. Institutions are also interested in knowing how likely it is that borrowers in a particular rating category will be upgraded or downgraded to a different rating, and especially, how likely it is that they will default. *Transition probabilities* offer one way to characterize the past changes in credit quality of obligors (typically firms), and are cardinal inputs to many risk management applications.

Default is not an abrupt process; a firm's credit worthiness and asset quality declines gradually. Transition probability is the chance of credit quality of a firm improving or worsening. The transition matrix thus represents moving probabilities from one rating level to all other ratings, including default for a given rating and time horizon (say one year). It shows the complete possible states that a rating can take over a given time horizon and therefore, provides detailed information on rating movements. Changes in distribution of ratings provide a much richer picture of changes in aggregate credit quality. When credit quality of corporate bonds worsens, the probability of future default also increases.

Rating transitions punctuate changes in the prices of securities issued by firms. Firms such as Moody's and Standard & Poor's announce ratings changes during periodic reviews of the creditworthiness of firms. There is now a vast history of rating transitions data summarized into rating transition matrices.

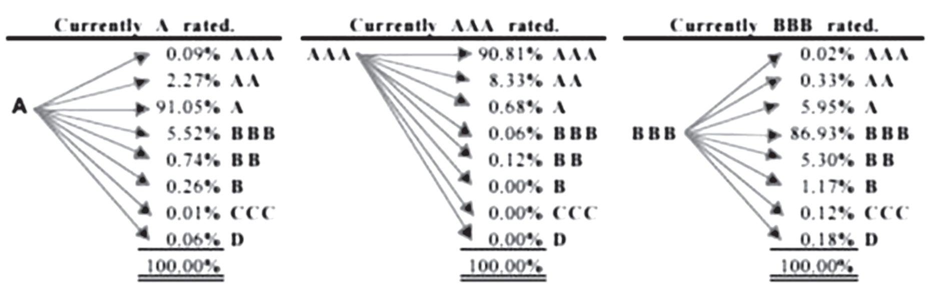
Rating transitions are important for market players for many reasons. First, they signal real changes in the value of firms resulting in a series of re-pricing of issued securities. Second, they impact investment portfolios subject to rating-based restrictions. For example, money market funds are not allowed to hold more than a small fraction of low-grade paper. Third securities that are indexed to rating are impacted. Credit sensitive notes for example, are bonds whose coupons are indexed to rating levels. Fourth, credit portfolio risk is simulated according to rating transitions. Hence, ratings are important in all aspects of the credit markets.

Figure 1 demonstrates some important features of a rating transition matrix. It shows the complete possible states a rating can take over the time horizon, say one year. Such a square array is termed as the matrix of transition probabilities. Information at only two dates for each year of data is necessary to calculate such a transition matrix. Essentially, the measurement of risk as a result of the rating changes was captured by a transition matrix where the probability of rating changes are assigned a number as shown below.

Table 7:
Rating Analysis of the Issuances of Fixed Rate Corporate Bonds

Initial Ratings	Rating at year-end (%)							
	AAA	AA	A	BBB	BB	B	CCC	Default
AAA	90.81	8.33	0.68	0.06	0.12	0	0	0
AA	0.70	90.65	7.79	0.64	0.06	0.14	0.02	0
A	0.09	2.27	91.05	5.52	0.74	0.26	0.01	0.06
BBB	0.02	0.33	5.95	86.93	5.30	1.17	0.12	0.18
BB	0.03	0.14	0.67	7.73	80.53	8.84	1.00	1.06
B	0	0.11	0.24	0.43	6.48	83.46	4.07	5.20
CCC	0.22	0	0.22	1.30	2.38	11.24	64.86	19.79

Figure 1: Examples of credit quality migrations (one-year risk horizon)



Source: Credit Metrics Technical Document (J P Morgan, 2007)

Literature Review

Credit rating migration modelling is an essential tool in credit risk analysis. A change in rating indicates that the perceived credit quality of an issuer has either improved (i.e. rating upgrade) or deteriorated (i.e. rating downgrade). The earliest credit risk modelling literature focused more on the prediction and explanation of corporate bankruptcies (Beaver, 1966; Altman, 1968).

In rating migration models, the correct estimation of transition probabilities plays a crucial role. Often, these probabilities are grouped in matrices. For modelling purposes, transition matrices are often assumed to follow a first-order Markov process (Jarrow et al., 1997). This implies that only the current rating grade is relevant in determining future migration probabilities; hence, ignoring historical information. In addition, migration probabilities are believed to be constant through time, known as the time-homogeneity assumption. A simple, time-homogeneous Markov model allows for the specification of the stochastic processes in terms of transition probabilities.

The Markov and time-homogeneity property only holds within one- or two-year horizons (Jafry & Schuermann, 2004; Kiefer & Larson, 2007; Frydman & Schuermann, 2008). Furthermore, there is overwhelming academic evidence that the rating process is non-Markovian and not time-homogeneous in the long run. For example, Altman & Kao (1992); Kavvathas (2000); Lando & Skødeberg (2002); Hamilton & Cantor (2004); Christensen et al. (2004); Frydman & Schuermann (2008); Figlewski et al. (2012) report the existence of a momentum effect in ratings.

Nickell et al. (2000) fit an ordered probit model and conclude that rating transition probabilities vary according to the state of the macro-economy. Using survival analysis, Kavvathas (2000) reaches the same conclusion. Bangia et al. (2002) divide the economy into two regimes, expansion and contraction, and condition the migration matrix on these states. They find that ratings migration probabilities vary with the business cycle. Frydman & Schuermann (2008) employ Markov mixture models, estimating two economic regimes, and find that ratings are not time-homogeneous after controlling for the state of the macro-economy. Figlewski et al. (2012) analyze macro-economic and ratings history related factors by applying survival analysis and decide that these factors are significant in explaining rating transitions.

Estimation of Transition Matrix

In this paper, we discuss two estimation procedures built on historical transitions: the Cohort approach and the hazard approach. The cohort approach is a traditional technique that estimates transition probabilities through historical transition frequencies. Though widely established, the cohort approach does not make full use of the available data. The estimates are not affected by the timing and sequencing of transitions within a year. An approach that circumvents such problems and makes efficient use of the data would be to estimate transition rates using a hazard rate approach. A cohort comprises all obligors holding a given rating at the start of a given period. In the cohort approach, the transition matrix is filled with empirical transition frequencies that are computed as follows. Let Ni,t denote the number of obligors in category i at the beginning of period t (Ni,t is therefore the size for the cohort i, t). Let Nij,t denote the number of obligors from the cohort i, t that have obtained grade j at the end of period t. The transition frequencies in period t are computed as

$$\hat{P}_{ij,t} = \frac{N_{ij,t}}{N_{i,t}}$$

Usually a transition matrix is estimated with data from several periods. A common way of averaging the period transition frequencies is the obligor-weighted average which uses the number of obligors in a cohort as weights:

$$\hat{P}_{ij} = \frac{\sum_t N_{i,t}\,\hat{P}_{ij,t}}{\sum_t N_{i,t}}$$

Inserting (1) into (2) leads to:

$$\hat{P}_{ij} = \frac{\sum_t N_{i,t}\,\frac{N_{ij,t}}{N_{i,t}}}{\sum_t N_{i,t}} = \frac{\sum_t N_{ij,t}}{\sum_t N_{i,t}} = \frac{N_{ij}}{N_i}$$

Therefore, the obligor-weighted average can be directly obtained by dividing the overall sum of transitions from i to j by the overall number of obligors that were in grade i at the start of the considered periods.

An alternative approach which captures within-period transitions is called the duration or hazard rate approach. In the following, we demonstrate its implementation without explaining the underlying theory. We first estimate a so-called generator matrix providing a general description of the transition behaviour. The off-diagonal entries of Λ estimated over the period [t0, t] are given as:

$$\lambda_{ij} = \frac{N_{ij}}{\int_{t0}^{t} Y_i(s)ds} \ for i \neq j$$

Where N_{ij} is the observed number of transitions from i to j during the time period considered in the analysis and $Y_i(s)$ is the number of firms rated i at time s. The denominator therefore contains the number of obligor-years spent in rating class i. Note the similarity to the cohort approach. In both cases, we divide the number of transitions by a measure of how many obligors are at risk of experiencing the transition. In the cohort approach, we count the obligors at discrete points in time (the cohort formation dates); in the hazard approach, we count the obligors at any point of time. The on-diagonal entries are constructed as the negative value of the sum of the λ_{ij} per row:

$$\lambda_{ij} = -\sum_{i \neq j} \lambda_{ij}$$

From Markov chain mechanics, a T-year transition matrix P(T) is derived from the generator matrix as follows;

$$P(T) = \exp(\Lambda T) = \sum_{k=0}^{\infty} \frac{\Lambda^k T^k}{k!}$$

Where ΛT is the generator matrix multiplied by the scalar T and exp() is the matrix exponential function. If we want a one-year matrix, we simply evaluate exp(Λ) but generating matrices for other horizons is just as easy. The one-year transition matrix based on this generator is given by applying the exponential function to the generator. Assuming for a moment that we have just four categories including default and NR, the matrix exponential exp(ΛT) would then be of the form:

$$\exp(\Lambda T) = \begin{bmatrix} 1000 \\ 0100 \\ 0010 \\ 0001 \end{bmatrix} + T \begin{bmatrix} \lambda_{11}\lambda_{12}\lambda_{13}\lambda_{14} \\ \lambda_{21}\lambda_{22}\lambda_{23}\lambda_{24} \\ \lambda_{31}\lambda_{32}\lambda_{33}\lambda_{34} \\ \lambda_{41}\lambda_{42}\lambda_{43}\lambda_{44} \end{bmatrix}$$

$$+ \frac{T^2}{2!} \begin{bmatrix} \lambda_{11}\lambda_{12}\lambda_{13}\lambda_{14} \\ \lambda_{21}\lambda_{22}\lambda_{23}\lambda_{24} \\ \lambda_{31}\lambda_{32}\lambda_{33}\lambda_{34} \\ \lambda_{41}\lambda_{42}\lambda_{43}\lambda_{44} \end{bmatrix} + \sum_{k=3}^{\infty} \frac{(\wedge T)^k}{k!}$$

We can evaluate the matrix exponential by truncating the infinite sum at some suitable point. In our application, we have to evaluate the matrix exponential of a special type of matrix, the generator matrix. On the diagonal, the generator matrix has negative values equal to minus the sum of the off-diagonal elements in the respective row. Adding up large positive and negative numbers can lead to numerical problems, in turn, rendering the truncated sum unreliable. To avoid such a programmed function which adjusts the generator to contain only positive values, the idea is as follows:

We first find the maximal absolute on-diagonal element of array1; denote this by $\lambda^{\max}$

$$\lambda^{\max} = \max\{|\lambda_{ii}|\}$$

Then, we construct a diagonal matrix D = diag ($\lambda^{\max}$) with $\lambda^{\max}$ as entries, i.e. multiply the identity matrix by $\lambda^{\max}$. Here, D is shown for the case of a 4 x 4 matrix:

$$D = \begin{pmatrix} \lambda^{max} & 0 & 0 & 0 \\ 0 & \lambda^{max} & 0 & 0 \\ 0 & 0 & \lambda^{max} & 0 \\ 0 & 0 & 0 & \lambda^{max} \end{pmatrix}$$

The sum of the generator itself and the thus obtained diagonal matrix contains only positive entries. Let us call this matrix Λ^* with $\Lambda^* = \Lambda + D$. Since the identity matrix commutes with any other matrix, we obtain:

$\text{Exp}(\Lambda) = \exp(\Lambda^* - D) = \exp(\Lambda^*) \times \exp(-D) = \exp(-\lambda^{\max}) \times \exp(\Lambda^*)$

We have therefore reduced our problem to that of the matrix exponential of Λ^* with only positive entries.

DATA DESCRIPTION

Ratings are based on the following alphanumeric scale: AAA (highest creditworthiness), AA, A, BBB, BB, B, C, D (default); for the symbols "AA" to "C" the modifiers "+" and "-" are used to indicate the relative strength within the rating categories concerned. The variable *Issuer Rating* exhibits variation at the issuer-rater-year level and is defined as follows.

We first assign numerical values to the alphanumeric debt instrument ratings with a value of one denoting the highest credit rating "AAA" and the value 18 denoting "D". Our sample spans 5 years 2012 -2017. Credit ratings are available from CRISIL, ICRA, CARE, Brickwork and India Ratings. We decide to only concentrate on the ratings of ICRA and focussed on non-structured instruments that are assigned long term credit ratings. Data for credit rating changes is collected from Bloomberg database. Data consists of 2,575 companies and their respective credit rating transitions year-wise. The total number of ratings covered in the database is 5,000. Year-wise break up for the five-year period credit rating category wise is shown in Table 10. Credit transition sample from the data can be seen as follows:

Table 9:
Sample Data from Bloomberg

Company Name	Date	Rating
20 Microns Nano Minerals Ltd.	8-Feb-13	BBB-
24/7 Customer Pvt. Ltd.	6-Dec-13	BBB+
24/7 Customer Pvt. Ltd.	16-Dec-14	BBB+
24/7 Customer Pvt. Ltd.	28-Apr-15	BBB+
3 F Industries Ltd.	8-Jan-13	BBB+
3 F Industries Ltd.	17-Jun-14	BBB+
3 F Industries Ltd.	20-Nov-15	BBB+
A 2 Z Infra Engg. Ltd.	31-Dec-15	D
A 2 Z Infraservices Ltd.	8-Jan-15	BB
A B C India Ltd.	7-Mar-14	BBB
A B C India Ltd.	3-Apr-15	BBB
A B T Ltd.	22-Apr-15	B
A C I L Ltd.	16-Apr-14	A
A C I L Ltd.	7-Aug-15	A

Table 10:
Year-Wise Break Up of Ratings Data

	2012	2013	2014	2015	2016	2017	Sum
AAA	4	4	15	14	5	1	43
AA+	10	4	18	16	11	2	61
AA	13	16	34	28	27	13	131
AA-	12	17	32	31	39	6	137
A+	40	23	35	64	48	3	213
A	28	50	40	48	33	7	206
A-	25	40	68	58	59	13	263
B+	69	70	41	32	27	5	244
B	42	49	37	20	18	0	166
B-	19	27	12	7	7	1	73
BB+	112	101	84	52	58	2	409
BB	86	112	64	50	34	5	351
BB-	55	77	43	38	30	3	246
BBB+	57	84	66	85	49	8	349
BBB	83	80	99	85	67	15	429
BBB-	94	127	102	85	54	7	469
C	9	26	26	12	9	2	84
D	70	66	55	75	53	3	322
NR	47	50	169	172	357	9	804
	875	1023	1040	972	985	105	5000

Table 11:
Sample Compiled Data Table

Id No.	Date	Rating Symbol	Rating Number
1	8-Feb-13	BBB-	4
2	6-Dec-13	BBB+	4
3	8-Jan-13	BBB+	4
3	16-Dec-14	BBB+	4
3	28-Apr-15	BBB+	4
4	17-Jun-14	BBB+	4
4	20-Nov-15	BBB+	4
4	31-Dec-15	D	8
5	8-Jan-15	BB	5
6	7-Mar-14	BBB	4

For calculation simplicity, companies have been identified by specifying 'ID No.'. The rating symbols have been grouped into 'Rating Number' as explained below:

Table 12:
Rating Categories

Rating Symbol		Rating Number	Rating Symbol		Rating Number
NR	0	0	BBB	9	4
AAA	1	1	BBB-	10	4
AA+	2	2	BB+	11	5
AA	3	2	BB	12	5
AA-	4	2	BB-	13	5
A+	5	3	B+	14	6
A	6	3	B	15	6
A-	7	3	B-	16	6
BBB+	8	4	C	17	7
		D	18	8	

Results & Interpretation

After running the VBA program of Cohort approach, we get the following result. The matrices mirror two empirical findings common to the matrices published by rating agencies. First, diagonal entries are the highest. This means the rating system is relatively stable. Second, default frequencies for the best two-rating classes are zero.

Cohort Approach

1-Year Transition Matrix

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	96.49%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.51%
AA	2	0.26%	97.66%	1.04%	0.26%	0.00%	0.00%	0.00%	0.00%	0.78%
A	3	0.00%	2.41%	92.76%	1.45%	0.12%	0.12%	0.00%	0.24%	2.90%
BBB	4	0.00%	0.27%	3.68%	88.84%	1.79%	0.33%	0.00%	0.76%	4.33%
BB	5	0.00%	0.00%	0.35%	3.70%	85.03%	1.21%	0.12%	1.85%	7.75%
B	6	0.00%	0.00%	0.12%	0.12%	3.74%	84.00%	1.17%	3.50%	7.36%
C	7	0.00%	0.00%	0.00%	0.00%	2.56%	4.27%	75.21%	10.26%	7.69%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

2-Year Transition Matrix

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	93.11%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	6.89%
AA	2	0.51%	95.39%	1.99%	0.50%	0.01%	0.00%	0.00%	0.00%	1.59%
A	3	0.01%	4.60%	86.13%	2.64%	0.24%	0.22%	0.00%	0.48%	5.68%
BBB	4	0.00%	0.59%	6.70%	79.05%	3.12%	0.59%	0.01%	1.49%	8.45%
BB	5	0.00%	0.02%	0.75%	6.44%	72.41%	2.07%	0.20%	3.51%	14.60%
B	6	0.00%	0.00%	0.22%	0.34%	6.35%	70.65%	1.86%	6.64%	13.93%
C	7	0.00%	0.00%	0.01%	0.10%	4.27%	6.83%	56.62%	18.17%	13.99%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

3-Year Transition Matrix

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	86.69%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	13.31%
AA	2	0.95%	91.09%	3.65%	0.93%	0.03%	0.01%	0.00%	0.03%	3.31%
A	3	0.03%	8.36%	74.45%	4.40%	0.48%	0.36%	0.01%	0.96%	10.94%
BBB	4	0.00%	1.34%	11.10%	62.87%	4.79%	0.96%	0.03%	2.84%	16.07%
BB	5	0.00%	0.10%	1.63%	9.78%	52.78%	3.01%	0.30%	6.32%	26.08%
B	6	0.00%	0.02%	0.42%	0.93%	9.18%	50.17%	2.39%	11.90%	25.00%
C	7	0.00%	0.00%	0.07%	0.43%	5.95%	8.79%	32.20%	29.06%	23.50%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

4-Year Transition Matrix

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	75.15%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	24.85%
AA	2	1.70%	83.30%	6.15%	1.59%	0.11%	0.04%	0.00%	0.11%	7.01%
A	3	0.14%	13.90%	56.23%	6.17%	0.86%	0.51%	0.02%	1.88%	20.29%
BBB	4	0.02%	3.00%	15.38%	40.50%	5.68%	1.27%	0.06%	5.16%	28.92%
BB	5	0.00%	0.42%	3.18%	11.41%	28.63%	3.23%	0.33%	10.39%	42.42%
B	6	0.00%	0.08%	0.78%	1.98%	9.64%	25.67%	1.99%	19.17%	40.69%
C	7	0.00%	0.02%	0.26%	1.08%	5.88%	7.42%	10.59%	39.85%	34.89%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

5-Year Transition Matrix

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	56.47%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	43.53%
AA	2	2.70%	70.29%	8.83%	2.36%	0.27%	0.10%	0.00%	0.43%	15.03%
A	3	0.42%	19.59%	33.46%	6.30%	1.15%	0.53%	0.03%	3.47%	35.07%
BBB	4	0.10%	5.88%	15.25%	18.07%	4.19%	1.11%	0.08%	8.40%	46.92%
BB	5	0.02%	1.26%	4.50%	8.16%	9.20%	1.94%	0.20%	14.76%	59.96%
B	6	0.00%	0.30%	1.26%	2.48%	5.47%	7.08%	0.76%	26.00%	56.66%
C	7	0.00%	0.12%	0.59%	1.39%	3.09%	2.90%	1.29%	46.17%	44.47%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

Hazard Rate Approach

The main point to note is that on-diagonal entries of the generator matrix are constructed as negative values of the sum of the entries per row. After running the VBA program of Hazard approach, we get the following result:

Generator Matrix

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	-0.140	0.084	0.000	0.000	0.000	0.000	0.000	0.000	0.056
AA	2	0.013	-0.112	0.071	0.013	0.003	0.000	0.000	0.000	0.013
A	3	0.000	0.039	-0.192	0.099	0.010	0.000	0.000	0.004	0.040
BBB	4	0.000	0.004	0.045	-0.164	0.054	0.004	0.000	0.009	0.048
BB	5	0.000	0.000	0.004	0.063	-0.206	0.025	0.003	0.028	0.082
B	6	0.000	0.000	0.001	0.003	0.058	-0.211	0.015	0.059	0.075
C	7	0.000	0.000	0.000	0.020	0.081	0.101	-0.525	0.222	0.101
D	8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NR	NR	0.005	0.017	0.059	0.172	0.216	0.125	0.015	0.081	-0.690

1-Year

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	87.00%	7.45%	0.38%	0.42%	0.46%	0.26%	0.03%	0.19%	3.81%
AA	2	1.12%	89.63%	6.17%	1.51%	0.40%	0.07%	0.01%	0.07%	1.03%
A	3	0.03%	3.37%	82.95%	8.63%	1.40%	0.22%	0.02%	0.54%	2.84%
BBB	4	0.01%	0.47%	3.91%	85.53%	4.95%	0.62%	0.03%	1.06%	3.41%
BB	5	0.02%	0.07%	0.62%	5.84%	82.26%	2.47%	0.28%	2.90%	5.55%
B	6	0.01%	0.05%	0.28%	0.93%	5.33%	81.42%	1.12%	5.75%	5.10%
C	7	0.02%	0.07%	0.26%	2.26%	6.64%	7.53%	59.25%	17.94%	6.04%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.34%	1.31%	4.23%	12.18%	14.70%	8.39%	0.89%	6.59%	51.37%

2-Year

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	75.78%	13.22%	1.29%	1.37%	1.41%	0.78%	0.08%	0.65%	5.42%
AA	2	1.99%	80.64%	10.75%	3.33%	1.00%	0.25%	0.02%	0.27%	1.75%
A	3	0.10%	5.89%	69.48%	15.02%	3.19%	0.69%	0.07%	1.33%	4.23%
BBB	4	0.04%	1.00%	6.80%	74.22%	8.89%	1.46%	0.10%	2.39%	5.09%
BB	5	0.05%	0.25%	1.49%	10.55%	68.93%	4.57%	0.48%	5.90%	7.78%
B	6	0.04%	0.18%	0.75%	2.54%	9.60%	66.95%	1.64%	11.13%	7.17%
C	7	0.05%	0.21%	0.78%	4.49%	10.80%	11.28%	35.26%	29.62%	7.52%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.49%	2.08%	6.35%	18.02%	20.82%	11.65%	1.13%	11.20%	28.25%

3-Year

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	66.10%	17.61%	2.47%	2.55%	2.49%	1.34%	0.13%	1.28%	6.01%
AA	2	2.64%	72.82%	14.11%	5.27%	1.74%	0.48%	0.05%	0.59%	2.30%
A	3	0.19%	7.76%	58.79%	19.64%	5.03%	1.25%	0.12%	2.30%	4.94%
BBB	4	0.07%	1.55%	8.88%	65.24%	11.92%	2.32%	0.17%	3.91%	5.93%
BB	5	0.08%	0.48%	2.44%	14.18%	58.66%	6.18%	0.60%	8.88%	8.49%
B	6	0.07%	0.34%	1.28%	4.34%	12.76%	55.49%	1.81%	16.05%	7.84%
C	7	0.08%	0.38%	1.35%	6.36%	13.16%	12.76%	21.11%	37.45%	7.35%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.55%	2.59%	7.46%	20.78%	22.97%	12.59%	1.12%	14.76%	17.17%

4-Year

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	57.72%	20.89%	3.77%	3.83%	3.55%	1.87%	0.18%	2.03%	6.16%
AA	2	3.13%	66.00%	16.52%	7.22%	2.56%	0.75%	0.07%	1.01%	2.74%
A	3	0.29%	9.11%	50.26%	22.89%	6.76%	1.82%	0.16%	3.40%	5.31%
BBB	4	0.11%	2.08%	10.35%	58.03%	14.17%	3.13%	0.24%	5.55%	6.33%
BB	5	0.12%	0.75%	3.35%	16.88%	50.61%	7.33%	0.67%	11.77%	8.53%
B	6	0.11%	0.52%	1.83%	6.09%	14.96%	46.32%	1.80%	20.51%	7.87%
C	7	0.11%	0.54%	1.87%	7.82%	14.32%	12.97%	12.76%	42.91%	6.69%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.58%	2.96%	8.07%	22.03%	23.31%	12.49%	1.03%	17.75%	11.77%

5-Year

		AAA	AA	A	BBB	BB	B	C	D	NR
		1	2	3	4	5	6	7	8	NR
AAA	1	50.48%	23.25%	5.07%	5.14%	4.53%	2.34%	0.21%	2.86%	6.12%
AA	2	3.48%	60.01%	18.20%	9.10%	3.42%	1.05%	0.09%	1.54%	3.11%
A	3	0.39%	10.06%	43.42%	25.12%	8.33%	2.37%	0.20%	4.60%	5.52%
BBB	4	0.16%	2.59%	11.35%	52.19%	15.80%	3.83%	0.30%	7.28%	6.51%
BB	5	0.15%	1.02%	4.18%	18.81%	44.21%	8.10%	0.71%	14.54%	8.29%
B	6	0.14%	0.70%	2.34%	7.68%	16.38%	38.93%	1.70%	24.52%	7.61%
C	7	0.13%	0.71%	2.34%	8.92%	14.72%	12.49%	7.81%	46.90%	5.99%
D	8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
NR	NR	0.59%	3.25%	8.42%	22.52%	22.86%	11.97%	0.93%	20.38%	9.07%

The main observation is that when we compare the two approaches, the hazard rate results show the probability of default for each category is slightly lower than the findings of the cohort approach. This is expected due to the richness of the hazard rate approach of using all data points compared to the cohort approach which does not use all the information.

Conclusion

The analysis of corporate credit quality is a major consideration in terms of investment evaluation. It is in the interest of investors to be aware of credit quality since no investor wishes to suffer loss due to decline in rating quality. Two indicators that can be monitored to evaluate credit quality are rating activity and rating drift. These two indicators can highlight rating movement trends and can provide an indication of the creditworthiness of bond issuers. This paper presents an estimation of credit quality transition matrices using both cohort approach and hazard rate approach. Being able to conduct this type of exercise becomes an important tool for lending institutions as they would be able to estimate and forecast the default probability of their debtors and the provisions they must hold.

Notes

1. The transition matrix methodology applied to credit ratings literature largely begins with Jarrow, Lando and Turnbull (1997) and further refinements made by Lando and Skodeberg (2002). Finding generator matrices with applications to credit ratings is credited to Israel et al (2001). Empirical stylized facts present in transition matrices are discussed by Altman et al (1992). The dependence of migrations on credit cycles is analyzed by Nickell et al. (2000).
2. The VBA codes used in this paper are largely modified versions of codes used by Loffler and Posch (2007).
3. The transition matrix methodology section largely draws from Loffler and Posch (2007).
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