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CRISIL RATINGS

The Most Reliable Opinion on Risk

insight in Risk

CRISIL Default Study 2005

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Box 1 : Default rates demystified

What are default rates?

For any given period, the default rate for a particular rating is the number of defaults among credits carrying that rating, as a percentage of all outstanding credits carrying that rating.

What are transition rates?

Transition rates indicate the probability of a given credit rating moving to other rating categories over a specified period of time.

Utility of default and transition rates

For all debt market participants, accurate and robust default and transition rates are critical inputs in the following decisions:

Pricing of debt

Default and transition rates are fundamental inputs to the pricing of a debt or loan. Default probabilities associated with ratings help investors/lenders in quantifying credit risk in their debt exposures, providing key inputs on whether to lend, how much to lend, and at what price. Transition rates are particularly helpful for investors who hold the instrument for a time horizon shorter than the maturity of the instrument.

Structuring and pricing of credit enhanced instruments

Structuring, rating and pricing of credit-enhanced products depend heavily on default and transition rates of underlying entities. The rapid growth of the structured finance market has made accurate computation of historical default and transition statistics imperative.

As critical inputs to credit risk measurement models

Default and transition rates are key inputs to many quantitative risk measurement models. Investors in rated paper can manage their risk exposures effectively if they have access to reliable default and transition rates.

Insights into the stability and meanings of ratings

Ratings are an indicator of probability of default. In a well-calibrated rating scale, the default rates should increase as one moves down the rating scale. Default and transition rates could be used to validate rating scales and quantify rating stability.

Key determinants of the accuracy and robustness of default and transition rates are the strength of the definition of default and the quality of the data set.

CRISIL's Definition of default

CRISIL defines default as any missed payment on a rated instrument***. This means that even a single day's delay, or a shortfall of even a single rupee, in terms of the promised payment schedule, would amount to a default.*** Any post-default recovery is not factored in by CRISIL's ratings as this is addressed through a separate recovery risk rating scale.

This rigorous and transparent definition of default provides a firm foundation for the study of CRISIL's default rates, and makes its default rates meaningful and reliable. The fact that this definition has been in place for several years, and is strictly applied, ensures that the data used for the present study is consistent. This rigorous approach underpins the validity of CRISIL's conclusions.

Given its observation that other rating services operating in India adopt varying approaches to the definition of default, CRISIL believes that this study provides unique and valuable insights to investors. It is important to contrast default studies using this digital approach to default, with those default studies that might use a more relaxed or inconsistent definition of default, which is likely to yield lower default rates. Some methodologies recognise default differently in their default studies and their external communication of ratings. Such studies would be less rigorous, and would therefore be less useful in pricing and provisioning decisions.

Most reliable data set in India

CRISIL's study of defaults draws on its ratings history of 14 years, across manufacturing, finance, and infrastructure sectors. CRISIL's data is the largest ratings database[1] available in India, encompassing over 4282 issuer-years. Significantly, it covers fourteen years between 1992 and 2005, and therefore includes data from periods of deteriorating as well as improving credit quality, across economic cycles. CRISIL's database is the most diverse such database available in India today. This is critical, as meaningful and robust default rates can only be based on an extensive and varied population.

Based on this data set, and a rigorous default definition, and having stood the test of various measures of validation, CRISIL's default rates are the most reliable estimate of default probability in the Indian market.

An analysis of CRISIL's default rates on calibration accuracy, predictive ability and stability rates is presented in the following pages.

[1] The data used for this analysis includes long-term ratings, and long-term ratings implicit in Fixed Deposit ratings, but excludes structured finance ratings and short-term ratings.

CRISIL Annual Default and Ratings Transition Study - 2005

CRISIL's annual default study for 2005 once again validates CRISIL's ratings as reliable measures of default probability. CRISIL's ratings continue to demonstrate ***high calibration accuracy*** with higher ratings translating into a lower likelihood of default. In addition, a high accuracy ratio of 0.80 continues to underpin these ratings' strong ***default prediction ability*** over the 14 years covered in the study. The ***stability rates*** of CRISIL's ratings have consistently improved over the years, and at 84 per cent compare well with stability rates of international rating agencies. In addition, for the first time in the Indian market, CRISIL is pleased to present an industry-wise classification of defaults over the last 14 years; this will further help debt market participants in finer pricing of securities.

CRISIL's study continues to highlight the declining trend in default rates. In fact, for the first time in the last decade, there has not been a single default in a calendar year (2005). Moreover, default rates observed over the last six years (2000-2005) for CRISIL-rated entities have been significantly lower than those over the 14 year period covered under the study, i.e. 1992-2005. The study is based on CRISIL's rating database spanning 14 years, across economic cycles. Because of the quality, depth, and size of this database, it continues to be the most robust in the Indian context.

CRISIL's default rates

CRISIL's default rates for the period 1992-2005 are presented below:

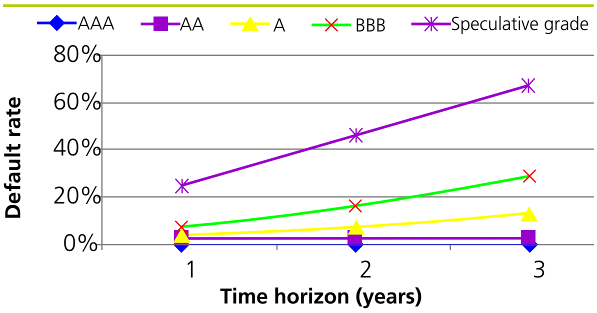
An analysis of CRISIL's default rates is presented in the following paragraphs.

Table 1: CRISIL Average Cumulative Default Rates (withdrawal-adjusted) (%), 1992-2005

Rating	Sample size	1-year	2-year	3-year
AAA	508	0.00	0.00	0.00
AA	1305	0.00	0.44	1.45
A	1401	1.00	4.29	9.00
BBB	617	3.40	9.49	17.26
Investment grade (AAA to BBB)	3831	0.91	3.19	6.39
Speculative grade	451	18.85	31.69	41.38

Source: CRISIL Database

Chart 1: CRISIL Average Cumulative Default rates (Withdrawal-adjusted), 1992-2005



Calibration Accuracy

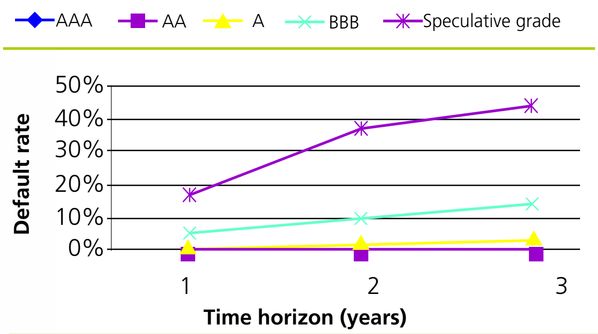
CRISIL's ratings continue to demonstrate a high degree of calibration accuracy. CRISIL's ratings being opinions on default risk, high ratings should translate into low default rates. The inverse correlation between CRISIL's credit ratings and default probabilities is evident from the chart and table above.

Table 2: CRISIL Average Cumulative Default Rates (Withdrawal-adjusted) (%), 2000-2005

Rating	Sample size	1-year	2-year	3-year
AAA	323	0.00	0.00	0.00
AA	535	0.00	0.25	0.59
A	298	0.67	1.66	3.16
BBB	117	4.27	7.63	10.61
Investment grade (AAA to BBB)	1273	0.55	1.10	1.71
Speculative Grade	176	11.93	27.47	29.81

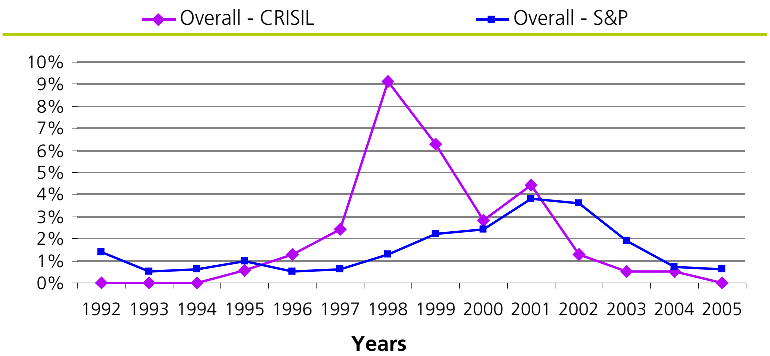
Source: CRISIL Database

Chart 2: CRISIL Average Cumulative Default rates (withdrawal-adjusted), 2000-2005



The movement of overall annual default rates (the proportion of total defaults to total outstanding ratings in a particular year) for CRISIL's ratings is shown in Chart 3. The statistics indicate that, since 1998, CRISIL's default rates have been steadily declining. Moreover, over the last six years, CRISIL's default rates have been comparable to those of Standard and Poor's (S&P) globally.

Chart 3. Overall Annual Default Rate



Source: CRISIL Ratings Database, Standard & Poor's Annual Global Corporate Default Study titled 'Annual 2005 Global Corporate Default Study and Rating Transitions' published on 31-01-2006

CRISIL's default rates for the last five years (2001-2005) stood at an average of 1.4 per cent, as against an average of 2.1 per cent observed over the entire 14-year period of this study (1992-2005). Moreover, about 70 per cent of defaults in CRISIL's portfolio, till date, occurred during the period 1997-1999, resulting in an upward bias for CRISIL's overall historical default rates.

Industry-wise Classification of defaults

For the first time in the Indian market, CRISIL is presenting an industry-wise analysis of defaults (Refer Table 3). This analysis highlights that four sectors accounted for about 50 per cent of the defaults on CRISIL-rated debt over the last 14 years.

Table 3: Industry - wise classification of Defaults

Industry	1992-94	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Non Banking Finance Company				4	13	3							20
Metals, mining,and steel			2	1	6	2	2	2					15
Textile				3	1	3	1	2		1			11
Consumer products		2	1	1	5				1				10
Chemicals				1	1	1	3	2	1				9
Construction and construction material			1		3	2	1	1					8
Automotive			1	1	2	1		1			1		7
Engineering					2	3	1	1					7
Pharmaceuticals			1		1	3		1					6
Paper & Paper Products				1	1	1			1				4
Diversified					3								3
Packaging					2	1							3
Power and power equipment							1	2					3
Sugar						3							3
Computers– Hardware					2								2
Miscellaneous					1		1						2
Telecommunication and related equipments					1	1							2
Courier & Express Services				1									1
Hotels						1							1
Oil & Refining						1							1
Printing						1							1
Shipping							1						1
Total Defaults	0	2	6	13	44	27	11	12	3	1	1	0	120
Number of ratings outstanding through the year	569*	345	467	540	483	429	388	271	233	198	186	173	4282

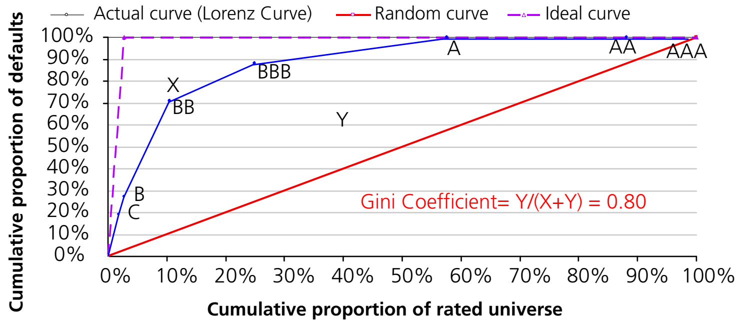
* The sum of the ratings for the year 1992, 1993 and 1994.

It is interesting to note that the majority of defaults occurred during the 1997-1999 period. This was due to the simultaneous occurrence of a number of events, including economic recession, and structural/ regulatory changes, especially in the financial sector. Although economic cycles will continue, CRISIL believes that structural and regulatory changes of this magnitude are unlikely in the future, thus rendering the possibility of a repeat of the 1997-1999 default rates remote. The table also highlights the robustness of CRISIL's dataset, which covers a down-cycle in credit quality (in the second half of the 1990s) and the current up-cycle in credit quality with very few defaults.

Predictive ability remains strong

CRISIL ratings also continue to strongly demonstrate their ability to predict defaults. Using data from 1992 to end-2005, the Gini coefficient for CRISIL's ratings is high at 0.80; this is only marginally lower than S&P's global average of 0.84.

Chart 4 - CRISIL Ratings: Performance in predicting default
One-year default rates (1992-2005)



Source: CRISIL Database

Box 2: How to read the Chart on the Gini Coefficient (Chart 4)

If ratings had no ability to predict default, then default rates and ratings would show no relationship. For example, assume 30 defaults occur in one year out of 1000 ratings (i.e. default rate of 3 per cent). In any randomly selected 100 companies (10 per cent of the rated population) one would expect to see 3 defaulted companies (10 per cent of defaulted population), since the number of defaults one would expect to observe in a sample is proportional to the selected number of companies. This is represented by the random curve, which will be a diagonal straight line. On the other hand if ratings are perfect predictors of default, then in the given example the worst 30 ratings should capture all the defaults. This is represented by the ideal curve. Since no rating system is perfect, the actual predictive power lies between these two extremes. The cumulative curve represents the actual experience. The closer the cumulative curve is to the ideal curve, the better the predictive power of the ratings. This is quantified by measuring the area between the cumulative curve and random curve (area 'Y' in the chart) in relation to the area between the ideal curve and random curve (area 'X'+'Y' in the chart). This ratio of Y/(X+Y), called the Gini coefficient or the accuracy ratio, will be close to 1 if ratings have excellent predictive ability, as the cumulative curve will almost coincide with the ideal curve. On the other hand it will be close to zero if ratings have poor predictive power, as in this case the cumulative curve will almost coincide with the random curve.

Definitions:

Cumulative default curve (Lorenz curve)

A plot of cumulative proportion of defaults, category-wise, against the total proportion of issuers up to that category. For instance, in Chart 4, 88 per cent of the defaults observed were in the BBB and lower categories; these categories had only 25 per cent of outstanding issuers. In other words, the bottom 25 per cent of issuers accounted for 88 per cent of all defaults that have taken place.

Random curve

A plot of cumulative proportion of issuers against the cumulative proportion of defaulters, assuming that defaults are equally distributed across rating categories. In such a plot, the bottom 25 per cent of issuers would account for exactly 25 per cent of defaults; the plot would therefore be a diagonal straight line, and ratings would have zero predictive value.

Ideal curve

A plot of the cumulative proportion of issuers against the cumulative proportion of defaulters, if ratings were perfectly rank-ordered, so that all defaults occurred only among the lowest-rated entities. Since 120 defaults have occurred across 4282 issuer-years, implying an overall default rate of 2.80 per cent, the bottom 2.80 per cent of issuers would have accounted for all the defaults if ratings were perfect default predictors, and any rating categories above this level would have no defaults at all.

Gini coefficient

Gini coefficient = (Area between Lorenz curve and random curve) / (Area between ideal curve and random curve)

Improvement in stability rates

Stability rates are a measure of the historically observed probability of ratings remaining unchanged, i.e. not showing any transition over a given time horizon (the shaded diagonal of Table 4 gives the stability rates of different rating categories). Transition rates indicate the probability of a given rating moving to other rating categories. Transition rates are thus particularly relevant for investors with time horizons shorter than the maturity of the debt instruments they hold, and for investors who need to regularly mark their investments to market.

Table 4 presents CRISIL's one year average transition rates for the period 1992-2005.

Table 4
CRISIL One Year Transition Rates
Withdrawal Adjusted (1992-2005)

(in percentage)

	Sample size	AAA	AA	A	BBB	BB	B	C	D
AAA	508	97.24	2.76	0.00	0.00	0.00	0.00	0.00	0.00
AA	1305	2.45	89.66	6.74	0.61	0.38	0.15	0.00	0.00
A	1401	0.00	3.78	82.37	7.42	4.50	0.21	0.71	1.00
BBB	617	0.00	0.32	5.67	73.26	14.10	1.30	1.94	3.40
BB	336	0.00	0.60	0.00	1.79	75.00	1.79	5.36	15.48
B	34	0.00	0.00	0.00	5.88	0.00	55.88	8.82	29.41
C	81	0.00	0.00	0.00	1.23	0.00	0.00	70.37	28.40

Source: CRISIL Database

CRISIL's one-year average stability rates[2] have been higher for higher rating categories. The overall stability rates of CRISIL's ratings have improved compared to previous one-year averages. This is highlighted in Table 5.

Table 5
CRISIL's One - Year Average Stability Rates

(in percentage)

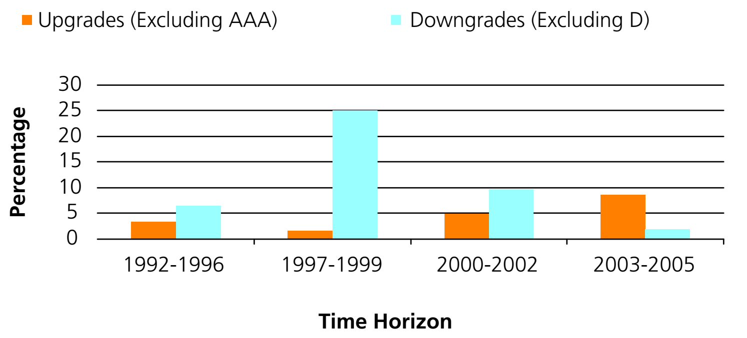
Data Set	AAA	AA	A	BBB	Overall*
1992 - 2005	97.2	89.7	82.4	73.3	84.0
1992 - 2004	96.9	89.3	82.4	73.2	83.6
1992- 2003	96.4	89.2	82.3	73.3	83.2
1992 - 2002	96.4	88.5	82.2	73.7	82.8

* All Non - Default catagory Ratings
Source: CRISIL Database

[2] The stability rate can be understood as the likelihood of no transition. The diagonal elements in the transition matrix indicate the stability rates for various rating categories. For example, Table 4 tells us that on an average 89.66 per cent of AAs have remained at AA, 2.45 per cent have been upgraded to AAA, and only 7.89 per cent have been downgraded, in any one-year period.

As with CRISIL's default rates, its one-year transition rates are reliable because they have been compiled over a long time frame (1992-2005), and cover a complete credit quality cycle. Chart 5 illustrates different periods of decreasing and improving credit quality, marked by increase and decrease in the percentage of downgrades.

Chart - 5 Percentage Of Upgrades and Downgrades



Source: CRISIL Database

Conclusion: CRISIL's default and transition rates - Robust and Reliable

The calibration accuracy, predictive ability, and stability of CRISIL's ratings demonstrate the strength of CRISIL's rating processes. These processes have been set up, stabilised, and refined in the light of CRISIL's seventeen years of rating experience, and their robustness is today recognised by both issuers and investors. This study presents empirical evidence that CRISIL's ratings are well-calibrated and have shown a track record of good predictive ability. The study is based on CRISIL's rating database spanning 14 years and covering a complete credit quality cycle. The quality, depth and size of this database continue to make it the most robust in the Indian context.

Annexure 1: Default and Transition rate Methodology

Concept of static pools

A static pool of a year is a set of companies having a given rating outstanding at the beginning of that year. Once formed, the pool does not admit any new members. For a company to be included in an n-year static pool, its rating has to be outstanding through the entire n years. Companies that withdraw or default in between will remain withdrawn or in default for the remaining years. Therefore a withdrawn company that is subsequently rated again, or a company from the pool that defaults and recovers, is not considered for re-inclusion in the pool. A company that remains rated for more than one year is counted as many times as the number of years over which it was rated. The methodology assumes that all ratings are kept current through an ongoing surveillance process, which in CRISIL's case is one of the cornerstones of the ratings value proposition.

For instance, a company continually rated from 1 January, 1995, to 1 January, 2000, would appear in five consecutive static pools, whereas a company first appearing on 1 January, 2002, and having an outstanding rating till 1 January, 2003, will only appear in the 2002 static pool. As this analysis is for annual default/transition statistics, only the net effect of multiple rating changes, if any, in a year is recorded.

Marginal default rate

Notations:

For CRISIL's data,

Y: Year of formation of the static pool (1992 to 2004)

R: A given rating category on the Rating Scale (AAA to C)

t: Years from the formation of the static pool (1,2,3, 4….)

$M_t^Y(R)$ = defaults from rating category 'R' in t^{th} year of Y-year static pool

$N_t^Y(R)$ = Non-defaulted ratings outstanding in t^{th} year in rating category 'R' from the Y-year static pool

Illustration[3]: Consider a hypothetical static pool formed in the year 1985, and having 100 companies outstanding at a rating of 'BB' at the beginning of the year. Suppose, out of this pool, there is one default in the first year, three in the second year, and none in the third year. Also assume there are no withdrawals in any year. Then, using the above notation,

$M_1^{(1985)}(BB) = 1$, $M_2^{(1985)}(BB) = 3$, and $M_3^{(1985)}(BB) = 0$

$N_1^{(1985)}(BB) = 100$, $N_2^{(1985)}(BB) = 99$, and $N_3^{(1985)}(BB) = 96$

For rating category 'R', the t^{th} year marginal default rate for Y-year static pool is the probability of a firm, in the static pool formed at the starting of the year Y, surviving till the end of period (t-1) and defaulting only in year t.

Mathematically, the marginal default rate for category 'R' in year t from Y static pool, $MDR_t^Y(R)$, is defined as

$MDR_t^Y(R) = M_t^Y(R) / N_t^Y(R)$

Therefore, $MDR_1^{1985}(BB) = M_1^{1985}(BB)/ N_1^{1985}(BB) = 1/100 = 0.01$

[3] This illustration is for explanatory purposes only, and does not indicate the actual or observed probabilities of default in any rating category

Cumulative Average default rate

The concept of survival analysis is used to compute the cumulative default probabilities. We calculate the cumulative probability of a firm defaulting as follows:

The cumulative probability of a firm defaulting by the end of (t+1) years	=	[Cumulative probability of the firm defaulting by the end of t years + Probability of the firm defaulting in (t+1) th year]

Further, for a firm to default in the (t+1)th year, it should survive till the end of t years. So,

Probability of the firm defaulting in (t+1)th year	=	[Probability of the firm surviving till end of tth year * Marginal Probability of the firm defaulting in (t+1)th year]

Now,

Probability of the firm surviving till the end of tth year	=	1- Cumulative probability of the firm defaulting by the end of t years

Hence,

Probability of the firm defaulting in (t+1)th year	=	[(1- Cumulative probability of the firm defaulting by the end of t years) * Marginal Probability of the firm defaulting in (t+1)th year]

Therefore, returning to the first expression,

The cumulative probability that a firm defaults by the end of (t+1) years	=	Cumulative probability of the firm defaulting by the end of t years	+	[(1- Cumulative probability of the firm defaulting by the end of t years) * (Marginal Probability of the firm defaulting in (t+1)th year)]

Restating the above in notation, if **$CPD_{(t+1)}(R)$** = cumulative default probability of a firm rated R defaulting in t+1 years, then,

$CPD_t(R) = MDR_t(R)$; for t=1

$CPD_{(t+1)}(R) = CPD_t(R) + (1 - CPD_t(R)) * MDR_{(t+1)}(R)$; for t=2,3….5 etc.

This iterative computation is repeated for all static pools, and a weighted average (weighted by the category-wise sample sizes) is taken to compute the overall default rate.

Withdrawal adjustment

In the year subsequent to its having obtained the rating, the firm can move to three different states - it can be timely on payments (and have a non-default rating outstanding), can default, or can repay the debt and withdraw the rating. As firms are not monitored post-withdrawal, the 'true state' (whether default or no default) of a firm whose rating has been withdrawn remains unknown in subsequent years. Therefore, a modified $MDR_t^Y(R)$ that ignores withdrawn firms is an appropriate measure of marginal default probability. As mentioned earlier, $N_t^Y(R)$ is also adjusted for the firms that belong to the static pool and have defaulted by the start of year t. The modified $N_t^Y(R)$ is:

$N_t^Y(R) =$ Number of firms in the static pool formed at the starting of year Y with rating category R

– Number of defaults till the end of period (t-1)

– Number of withdrawn firms till end of period t.

As reliable information meeting CRISIL's stringent requirements is not available post-withdrawal, withdrawal-adjusted default rates have been used for this study.

Post-default return of a firm

Post-default, firms sometimes recover and, consequently, receive a non-default rating in subsequent years. As CRISIL's credit rating is an indicator of the probability of default, default is considered an "absorbing state" i.e. a firm cannot come back to its original static pool post-default. In static pool methodology, the recovered firm is considered a new firm which, if it continues to be rated, appears in the static pool of the year in which it recovered.

Methodology for transition rates

The t-year transition rate (from rating R1 to rating R2) for the static pool formed at the start of year Y, is the proportion of firms rated R1 at the beginning of static pool, that are found to be in R2 at the end of t years. This proportion is called the t-year transition probability from R1 to R2. The t-year transition matrix is formed by computing transition probabilities from various rating categories (except D) to other rating categories.

Withdrawal-adjusted transition rates are computed as mentioned above, but excluding companies that are withdrawn at the end of the t years.

In computation of t-year transition rates, ratings at a point of time, and at the end of the t^{th} year thereafter, are considered. Therefore, the firm does not drop out of the sample when withdrawn in between.

CRISIL Ratings

CRISIL Ratings is India's most influential and the world's fourth largest ratings agency - the most reliable opinion on risk. It is the market leader in India - shaping the development of the debt markets having rated over 5,600 debt instruments worth over Rs.7.79 trillion, issued by over 2,500 companies. CRISIL Ratings has created rating methodologies for debt instruments and innovative structures across sectors. It is the only rating agency in India operating on the basis of sector specialisation. CRISIL Ratings has a strategic working relationship with Standard & Poor's, CRISIL's majority shareholder and the world's foremost provider of independent credit ratings, indices, risk evaluation, investment research and data.

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