Under-estimation of Credit Risk in India by Conventional Credit Ratings:

An Empirical Study

Abstract

The prevailing method of credit risk assessment is founded upon the credit rating system. The ratings classify borrowers (typically companies) into grades of credit risk – starting from AAA for the safest borrowers that are least likely to default on their debt obligations to C for the borrowers that are highly likely to default. This likelihood is quantified by credit rating agencies. This enables an empirical study of the actual frequency of defaults vis-à-vis its expected value based on ratings. This paper summarizes the results of one such study undertaken by ASQI Systems.

The findings indicate that for the universe of listed companies about which rating data is available, the actual frequency of default is 2-4 times higher than expected frequency of default based on credit ratings, for the period of 10 years between 2009 and 2018.

We highlight several possible reasons for this mismatch, including rating shopping by borrowers, adverse bias in rating updates and lack of empirical updates of their models by agencies.

Method of research

Credit rating agencies routinely publish guiding estimates regarding the expected levels of default in each rating category – based on long term observations of the same in their own rated universe. We used one such publication to state the expected levels of default by rating (details available on request).

Next, we used the data available in public domain on listed companies – based on their submissions to the stock exchanges regarding their ratings as well as defaults. We considered data for a period of 10 years between 2009 and 2018. For each week, we arranged the companies in the category of their rating. Then we considered the event variable for default.

Default = 1 if the company is downgraded to default rating in the next 1 year

= 0 otherwise

We calculated the probability of default in each week for each rating cohort as follows.

pD = (Total instances of default in the cohort as defined above) / (Total instances in the cohort)

This was repeated for all the weeks from January 2009 to December 2018. We averaged the pD values for each month, each year and also at the aggregated level and juxtaposed these with the expected pD values as per the credit rating.

Results

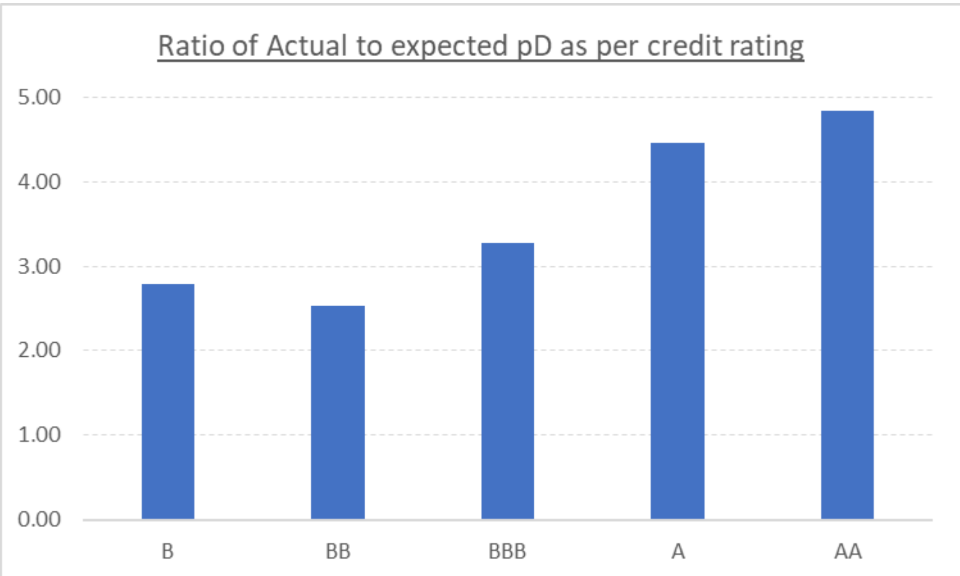
The summary across all years is as follows.

Rating	pD as per credit rating	Actual pD
B	8.0%	22.4%
BB	3.5%	8.9%
BBB	0.9%	2.8%
A	0.2%	0.9%
AA	0.02%	0.10%
AAA	0.00%	0.26%

The year-wise summary is as follows.

	B		BB		BBB		A		AA		AAA	
Year	pD CRA	Actual pD	pD CRA	Actual pD	pD CRA	Actual pD	pD CRA	Actual pD	pD CRA	Actual pD	pD CRA	Actual pD
2009	8.0%	14.3%	3.5%	8.7%	0.9%	0.9%	0.20%	0.32%	0.02%	0.13%	0.00%	2.41%
2010	8.0%	30.5%	3.5%	9.6%	0.9%	2.5%	0.20%	0.62%	0.02%	0.12%	0.00%	0.00%
2011	8.0%	29.6%	3.5%	17.4%	0.9%	4.0%	0.20%	1.09%	0.02%	0.00%	0.00%	0.00%
2012	8.0%	26.0%	3.5%	10.7%	0.9%	4.3%	0.20%	1.26%	0.02%	0.23%	0.00%	0.00%
2013	8.0%	21.3%	3.5%	5.6%	0.9%	2.4%	0.20%	0.63%	0.02%	0.02%	0.00%	0.00%
2014	8.0%	21.7%	3.5%	6.7%	0.9%	1.6%	0.20%	0.47%	0.02%	0.00%	0.00%	0.16%
2015	8.0%	23.6%	3.5%	11.7%	0.9%	3.6%	0.20%	1.23%	0.02%	0.19%	0.00%	0.03%
2016	8.0%	17.3%	3.5%	7.7%	0.9%	3.2%	0.20%	1.59%	0.02%	0.00%	0.00%	0.00%
2017	8.0%	22.5%	3.5%	6.4%	0.9%	2.6%	0.20%	0.76%	0.02%	0.11%	0.00%	0.00%
2018	8.0%	16.9%	3.5%	4.8%	0.9%	3.1%	0.20%	0.95%	0.02%	0.18%	0.00%	0.00%

The ratio of actual to expected probability of default ranges between 2.5 and 4.8 across ratings when taken as an average over the years. The below graph summarizes this.



Inferences

We can clearly infer the following from the above analysis.

1. The guidance about the long-term default probability as per the conventional credit rating significantly underestimates the actual probability of default.
2. This underestimation is pervasive across ratings – it is about 2.5 to 3.0 times for B, BB and BBB rated companies and a much worse 4.5 to 4.8 times for A and AA rated companies.
3. The underestimation is not based on one or two bad years. Except for AA rated companies, the minimum of the ratio of actual to estimated pD is above 1 for all other ratings. In other words, for all these ratings, across all years the conventional approach has always underestimated the credit risk.

Possible causes

There are several likely reasons for this significant underestimation of probability of default (and consequently the credit risk) of large majority of borrowers by credit rating agencies. We have suggested a few of these below. This list is by no means exhaustive.

1. Rating shopping
   There is an obvious conflict of interest at the heart of conventional credit rating process. When the revenue model of credit rating agency is to charge the very company it is supposed to rate, it is not difficult to imagine the divergent pulls of business development and analytical accuracy. We do not have specific insights into the processes followed by rating agencies and hence we will not be able to expound on this point further.
   However, a corollary of this phenomenon is lot easier to observe – namely rating shopping. Borrowers are free to choose their rating agency. While the industry structure of rating agency is oligopolistic, there is fair degree of competition amongst them to allow borrowers to shop for best possible rating for their given state of finances. While each particular case may be unique, at the level of the overall population of rated companies, this is likely to lead to a 'rating inflation' i.e. credit ratings that are higher than what they would have been without the prevalent revenue model of rating agencies. As our analysis in this paper indicates, such rating inflation is indeed the reality.
   More evidence of this phenomenon globally is available at the below links.
   a. https://www.researchgate.net/publication/228203856_The_Issuer-Pays_Rating_Model_and_Ratings_Inflation_Evidence_from_Corporate_Credit_Ratings
   b. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1703.pdf
   c. https://www.hbs.edu/faculty/Publication%20Files/09-051_13e0275c-a3a4-48bd-a86a-2324d5d70b57.pdf

2. Selective non-cooperation by borrower in providing data

   Credit rating agencies rely on the data provided by the borrower while rating it. This is also true for revising the rating. In general, borrowers are forthcoming about this data. However, it is not uncommon for borrowers to stop providing the data. Such non-cooperation generally results in only a 'suspension of rating' by the rating agency as against 'default'. While such behaviour on the part of borrowers may constitute breach of contract between the borrower and the rating agency, it shouldn't come as a surprise if one finds higher instances of non-cooperation amongst the eventual defaulters than amongst non-defaulters.

As a result, a rating agency dependent on borrower-provided data does not have enough to work with in highlighting deterioration in the financial health of the borrower and consequently its credit rating. In a utopian world where companies with deteriorating finances continue to provide data to rating agencies without fail, we may expect a rating downgrade of many such companies – which would reflect in improved (i.e. lower) actual default rates for higher ratings. That however still wouldn't solve for the overall inflation across the spectrum of ratings – it would only shift the problem to lower ratings. In any case, we don't live in such a utopian world!

3. Lack of usage of empirical methods by rating agencies

   This problem is partly linked to ratings inflation mentioned above. It would be logical for rating agencies to update their models at least annually to better reflect the actual instances of default over time. While many agencies do seem to undertake detailed analyses of their upgrades and downgrades as well as instances of default across categories, there are hardly any details available in public domain about a revision in their default rate forecasts by rating. One would think that given the publicly available data as well as a big trove of private data available with the agencies, this exercise would be fairly straightforward.

4. Financial shenanigans by borrowers

   This is based on Goodhart's law which states that "When a measure becomes a target, it ceases to be a good measure." The methodologies followed by rating agencies are well-known. While they appeal to common sense and use first principles well, they are also open to manipulation by the borrowers. Window-dressing of accounts to hide troubles in business is neither new nor unique to credit markets. In the context of credit rating, it is quite possible that a borrower is able to delay a downgrade in its rating long enough through accounting gimmickry that the eventual default happens at a rating better than what it would have been with full information.

5. Lack of usage of high-frequency macroeconomic data

   Most rating rationales focus largely on the borrower while paying at most lip-service to the macroeconomic context. As the equity markets testify, large part of the returns of a company's common stock are explained by the so-called 'beta'. This factor denotes the dependence of the stock returns on the returns of the overall market. The beta component of returns often explains a large proportion of total returns of the stock – the rest being explained by idiosyncratic factors. In other words, there is an inherent macro exposure in each company – which explains bulk of its performance. A similar approach can be used in credit risk assessment as well. It is common knowledge that defaults rise during recessions and fall during booms. Accordingly, a credit risk assessment process that pays adequate attention to high-frequency macro factors is likely to be better warned of impending turn in macro context.

Take-aways

Empirical evidence based on analysis of Indian companies in recent decade shows that conventional credit ratings understate the probability of default of companies. The underestimation is serious – of the order of 2 to 4 times. This is potentially on account of a conflicted revenue model of the rating agencies (leading to ratings inflation), selective non-cooperation by the near-default borrowers as well as financial shenanigans (i.e. window-dressing) by borrowers.

This under-estimation problem can be addressed by using alternate sources of credit risk assessment that are paid for by the user (i.e. lender) and using data available publicly as well as expanding the data sources to include high-frequency macroeconomic data and other alternate data. Lastly, emerging advances in analytical methods including those in machine learning can be used to improve forecasting process.

As ASQI, we have developed a forecasting engine that incorporates conventional as well as alternate data to forecast financial health of companies using advanced machine learning methods. In another white paper, we have explained how such forecasts outperform the estimates based on conventional credit rating. Please write to us as asqi.systems@asqi.in to know more.

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