A Review of Moody’s Methods Used to Assign Credit Ratings to Collaterized Loan Obligations

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August 11, 1998

Abstract: The methodology by which Moody’s assigns credit quality ratings to Collateralized Loan Obligations are examined. One key aspect of the process is the Moody’s Diversity Score, a metric for the level of diversification present in the portfolio of corporate loans the cash flow from which is dedicated to the servicing of the CLO debt. Even Moody’s recognizes this methodology as inadequate. To compensate for this weakness, Moody’s intentionally applies a series of overly conservative input assumptions for other aspects of their analysis. It is concluded that the credit quality ratings assigned by Moody’s to CLO instruments do not represent the same level of loss expectation as do the same ratings when assigned to other fixed income instruments such as corporate or municipal bonds.
Introduction

The purpose of this study is to review the methods employed by Moody’s in assigning credit quality ratings to Collateralized Loan Obligations (CLO).

The CLO

CLOs have become popular fixed income instruments in recent years. A CLO is a bond that is the debt obligation of a specially created entity (often called a “special purpose vehicle”). The assets of the vehicle consist of a portfolio of loans to corporations that are bought in the secondary market for bank loans, or as part of loan syndication. The funds to purchase the portfolio of loans are obtained by issuing the CLO bonds and by issuing an additional bond issue whose credit priority is subordinated to the CLO issue. Due to the additional funds arising from the subordinated debt, the face value of the loans is larger than the value of the debt outstanding on the senior CLO issue. For example, a package of $100M in loans may be financed with an $80M in senior CLOs and $20M in subordinated debt or equity. The cash flows from the loans are dedicated to servicing the CLO and subordinated debt.

Like any bond, one of the key aspects of a CLO is the credit quality rating which it has been assigned by rating agencies such as Moody’s, Fitch and Standard & Poor’s. CLO debt normally carries a credit rating that is higher than the average credit rating of the individual loans which make up the loan portfolio. There are two reasons for this. Firstly, the loan portfolio is diversified across a number of borrowers, lessening the likelihood of a total default, as compared to a loan or bond from a single borrower. Secondly, the funds raised from the subordinated debt allow the loan portfolio to be larger than the CLO obligation debt – in other words, the CLO is more than 100% collateralized. As such, even if there are some defaults in the loan portfolio, the undefaulted portion of the loan portfolio should be sufficient to make timely payment of interest and principal on the CLO obligations. The key question is how large should the subordinated debt be in order to qualify for a given credit rating.

Moody’s

Moody’s, Fitch and Standard & Poor’s are independent rating agencies. For a fee, they evaluate the creditworthiness of borrowers for bonds and loans. Among the borrowers to obtain such ratings are national governments, states, municipalities and large corporations. The information content of ratings and the process by which ratings are determined for different types of financial obligations and borrowers has been examined in Pogue and Sodofsky (1969) and Lovisek and Crowley (1990).

Of the rating agencies, Moody’s has been the most active in the CLO field. Accordingly, this paper is focused on the methodologies used by Moody’s to assign CLO ratings. Similar procedures are in place at Fitch and Standard & Poor’s. Backman and O’Connor (1995) explain the Moody’s methodology at length in an internal research paper.
The ratings consist of an alphanumerical scale that is intended to convey to investors an expectation of the losses that may occur from possible default on the part of the borrower. In simplest form, the expectation of losses due to default is merely the likelihood of default times the likely loss of value if default occurs. The complexity of the credit rating process arises from the difficulty in making accurate forecasts of the likelihood of default and the losses arising from default.

**Moody’s methodology**

- Evaluate credit worthiness of borrowers whose loans will be present in the portfolio
- Evaluate effect of diversification – (Moody’s proprietary “Diversity scores” system)
- Other Qualitative adjustments

Moody’s methodology begins with rating the creditworthiness of borrowers whose loans will be present in the portfolio. We have no comment on the process by which Moody’s assigns ratings to bank loan borrowers.

The second step in the procedure is to consider the diversification of the loans that make up the portfolio. This is the focus of our interest. Moody’s uses a proprietary system called “Diversity Scores” which summarizes into one number, the extent to which a loan portfolio is diversified across borrowers and industry groups. The purpose of diversification is to control the extent to which it is likely that defaults among borrowers would be correlated and hence likely to occur concurrently rather than as independent events.

The Diversity Score system operates by quantifying the level of credit support (subordination) which is required to achieve a particular level of CLO credit rating given a loan portfolio of a given average quality rating and level of diversification by issuer and industry.

**Our Investigation**

- Moody’s observance of basic criteria required in evaluating diversification.
  - inter-industry correlation
  - intra-industry correlation
  - default risk
  - recovery rates
  - possibility of rating changes
- Generic Functional Form – can we reverse-engineer the methodology?
- Fitting Method – polynomial regression
Inter-industry / Intra-industry
The Diversity Score system does not explicitly take into account the correlation between borrowers or industry groups. For example, a loan portfolio consisting solely of banks and insurance companies (considered two different industries) would be considered as diversified as a portfolio consisting of oil companies (fuel producers) and truck transport (heavy fuel users). Nor does it take into account the correlation within an industry. For example, correlations among the three major auto manufacturers might reasonably be expected to be higher than across three high technology companies with vastly different products. It is particularly curious that Moody’s uses such an analytical system when Backman and O’Connor comment (in a Moody’s internal research paper!) “The degree to which bonds are default-correlated determines whether credit protection (appropriate fraction of subordinated debt) should be closer to 10% or 100%”.

The computational method for explicitly taking expected correlations of loan defaults into account is presented in Levin (1997). This model uses correlations among corporate asset levels to estimate the extent to which defaults should be correlated. The paper also correctly points out that the due to the skewed nature of fixed income returns (large loss upon default) the effect of correlation among defaults has a much more dramatic effect than would be present if returns were more normally distributed. It should be noted that the model presented assumes that when default occurs, the lender receives no recovery of value at all ( unrealistically accentuating skewness). In addition, the recent work of Hlawitschka and Stern (1995) suggests that from an investor utility viewpoint, skewness of distributions may not be economically meaningful for large portfolios even if the assets returns are highly skewed, as in the case of out-of-the-money call options. Hence Moody’s overestimate of the correlation between industry groups has a doubly biased effect.

Result: Default-Correlation is overestimated

Default Rates
The first way in which Moody’s attempts to compensate for the inexactness of the Diversity Score system is in the choice of basic default rate assumptions. Unfortunately, the secondary market for bank loans is a relatively recent phenomenon. As such, no large sample long-term studies are available with regard to the frequency of defaults for various credit ratings of bank loan. However, for each level of credit rating, extensive historical information on corporate bonds is available as to the frequency of defaults. This information is detailed in studies such as Moody’s own reports Carty and Lieberman, (January 1996), Carty and Fons (1993) as well as academic studies such as Altman (1997). Moody’s has chosen to handle this problem by substituting 10-year cumulative default rates on corporate bonds of a given rating class for the unknown loan default rates. Given that most of the loans underlying CLOs have maturities of three years or less, using cumulative default rates over an assumed 10 year life could well lead to some distortion. One could justify such a proxy by assuming that the overwhelming
majority of default events occur within the first three years of issuance, but such an assumption is not supported by other studies such as Altman (1997).

Result Default-Probability is overestimated

Recovery Rates

In the same fashion that Moody’s appears to overestimate the default frequency of loans in its expectation of loss calculations, it equally appears to overestimate the loss of value when default occurs. In both Moody’s own study, by Carty and Lieberman (November 1996) and in a separate study by Asarnow and Edwards (1995), the average recovery rate on defaulted bank loans is approximately 70%. The Moody’s study relied on loan prices from the secondary market in which market risk premia and bid/asked spreads make loan prices a downward biased estimate of recoveries.

Result: Recovery Rates are underestimated

In both studies, the distributions of the recovery rates on defaulted loans have large standard deviations (~20%) and negative skewness (average below median). It is standard practice statistics to use robust statistics for central tendency (such as median rather than means) when faced with small or skewed distributions. This would result in Moody’s using values in its process which are larger than the means noted above. They do just the opposite, using an assumed recovery rate of just 30%. In addition, the Moody’s analysis ignores the fact that not only does the diversification of the loan portfolio decrease the dispersion of the default rate, it also decreases the dispersion of the recovery rate. If we assume a portfolio of 100 loans of which 25 eventually default, the expected dispersion of the recovery rates would be the 20 / (25^.5) or just 4%. Given mean recoveries of 70%, an assumption of 30% would be more than eight standard deviations from the mean, with a likelihood of just one in several million.

Result: Dispersions of Default Probability & Recovery Rate are overestimated

Rating Changes

Austin (1992) and Altman (1997) also raise another important issue. The ratings on fixed income securities can change over time as issuers are upgraded and downgraded. The Moody’s analysis does not take into account the potential for such changes. Correcting this omission would be relatively more favorable to CLOs where the underlying collateral loans were of lower quality grades. While portfolios of lower quality loans are likely to contain both upgrades and downgrades, portfolios of high quality loans can only have downgrades. The failure to consider this issue in the analysis biases the result against issues with lower grade collateral. The methodological differences between studies can also have an important impact. In some studies by Moody’s and Standard & Poor’s, a method known as “static pools” is in use. Such static pool studies mix long seasoned bond issues with newly issued securities. Results in the Altman study suggest ratings
change relatively little in the first few years after issuance. Hence use of corporate bond rating transition matrices to capture the probability of upgrades and downgrades would exaggerate the extent that ratings would change on loans that tend to be of much shorter maturity.

**Result: Effect of Rating Changes Ignored (possible bias against lower grades)**

**Reverse-Engineering Functional Form**

We tested the robustness of the Diversity Scores by attempting to infer, from the tables in Backman and O’Connor, the nature of the mathematical functional form by which diversity scores become levels of credit protection. We attempted to fit equations of the following from to the data:

\[ C = a_0 + \sum_{j=1}^{n} a_j D^{(1/j)} \]

Where
- \( C \) = the credit level (subordination) required
- \( J \) = a positive integer
- \( D \) = diversity score
- \( a_j \) = the regression coefficients

The fitting process is known as polynomial regression. We were unable to fit Moody’s published data to satisfactory tolerances without using values for \( j > 5 \). Unfortunately, such functional forms were neither economically intuitive nor did they produce rational results for independent variables values outside the ranges specified in the tables.

Specifically, any reasonable function to measure diversification be monotonically decreasing over all positive domains of \( D \) (subordination required should never increase with diversification of the loan portfolio)

Many such fits (\( j>5 \)) lacked this basic property. Efforts were also made with multivariate functions of both diversity and loan credit quality, as well as exponential functions. No satisfactory results were obtained.

**Other Qualitative Adjustments**

In addition, Moody’s adds a subjective increment to these assumed cumulative default rates. The incremental adjustments are inconsistent from one quality grade to another, rather than either staying the same or rising smoothly as we decrease credit quality.

**Summary**

The methodology in use currently by Moody’s tends to overestimate the credit risk of CLOs by overestimating the risk of default, the correlation between and within industry groups, the dispersion of both default probabilities and recovery rates, and by
underestimating the recovery rate itself. In addition, Moody’s make no adjustment for the inherent adverse biasing effect due to the probability distribution of rating changes.

In addition to these concerns, we are unable to fit an economically meaningful functional form to the published data.

In conclusion, it seems clear that while it is possible that more than two “wrongs” will make a “right”, the use of Moody’s credit quality ratings for CLO issues does not reflect available best practices. Such ratings do not appear to convey the same expectations for risk of loss that the same rating would for another type of bond. The rating assigned to senior CLO issues with a specific proportion of subordinated debt is overly conservative.
References


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