MOODY'S ANALYTICS

Whitepaper

Moody's Market Implied Ratings: Description and Methodology

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Summary

Moody's Market Implied Ratings platform (MIR) provides relative credit risk and value signals from four sources, corporate bond, credit default swap (CDS), and equity markets, and Moody's ratings. This paper provides information about market-implied ratings and how they are calculated, as well as a summary of key analytical findings. It is an update of the previous methodology guide published in July 2016. Some key highlights from this publication are as follows:

- Market Implied Ratings date from 2002, when they were launched as an internal tool for Moody's ratings analysts. They have been publicly available to customers since 2003.
- MIR cover all entities with Moody's ratings and CDS, bond, and equity prices, including industrial, financial, utility, sovereign, and sub-sovereign entities. The implied ratings and benchmark credit curves are updated daily.
- Market-implied ratings are pure reflections of market trading levels of an issuer's securities relative to similarly rated securities. We do not calibrate the implied ratings models to achieve any desired outcomes.
- Around 80 percent of the time market trading levels "disagree" with Moody's Investor Service's ratings, i.e., the implied ratings derived from market prices of issuers' securities differ from the entities' MIS ratings.
- Changes in market implied ratings usually lead changes in Moody's ratings. This is not surprising, given markets' abilities to instantaneously incorporate new information about issuers' creditworthiness.
- Implied ratings are much more volatile than Moody's ratings. Thus, while they provide much more timely signals of changes in default risk, they do so at a cost of sometimes overreacting to price changes in the individual security or the market as whole.
- The Market Implied Ratings platform also has information useful for relative value investors. For example, it can be used to find bonds and CDS contracts that trade "cheaply" for their ratings.
- The 2018 version of Market Implied Ratings are calculated on the updated Senior Ratings Algorithm (SRA), which switches from a static notching rule to a dynamic one.

CONTENTS

I. Introduction

Agency ratings and market prices often provide different perspectives on a company's credit outlook. Leveraging market signals to enhance fundamental analysis in an efficient way has always been a challenge for market participants. Moody's Market Implied Ratings platform provides a simple framework to synthesize information and captures these disagreements over time between Moody's ratings and three valuation metrics from the bond, CDS and equity markets, to better identify changes in relative credit quality (Figure 1).

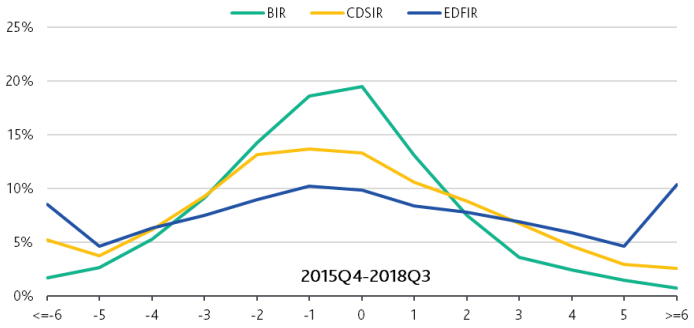
Variations in agency ratings and market signals reflect a number of factors. There are two major types of risk measures, point-in-time (PIT) metrics and through-the-cycle (TTC) metrics. PIT measures reflect the current state of the economic environment, as well as obligor specific information. Alternatively, TTC measures put more weight on longer-term trends than on cyclical factors, thus provide a stable indicator of creditworthiness. Market prices incorporate all available information and investor expectations at a given moment, including systematic and macroeconomic trends, so they are PIT indicators in nature. Such information changes constantly, making market-based risk signals more volatile. In contrast, agency ratings are TTC measures of credit risk, thus more stable. It is worth noting that the disagreements between market signals and Moody's can also reflect factors unrelated to credit risk, such as liquidity or investors' risk appetite.

A credit rating is just one of many opinions about an issuer's creditworthiness. Disagreements between Moody's credit ratings and other valuation and risk metrics have been around for a long time. Sometimes they simply reflect varying conclusions, arrived at by processes that are, by necessity, as much art as science. In other cases, the differences stem from factors related to the framework of analysis. Market-based metrics are better identifiers of default risk over the near term, but Moody's ratings are at least as good over longer periods.[1] And even if markets provided more timely and accurate signals on average, there is a cost in terms of the higher volatility of implied ratings compared to Moody's ratings.

One challenge in using market prices as signals of credit risk is to separate entity-specific signals from general market moves, because bond, CDS and equity prices all encompass both market-wide risk levels and entity-specific factors. By benchmarking individual companies to market-wide measures in the form of median credit spreads or median EDF, MIR remove the impact of systematic, market-wide shifts. A change in an implied rating purely reflects the perception of entity-specific - or idiosyncratic – risks. Compared to the typical PIT measures, changes in MIR are more likely to be associated with changes in issuers' long-term default risk profile, which will lead to Moody's rating changes eventually.

MIR alerts users to possible changes in creditworthiness at an early stage, leaving investors with enough time to perform additional analysis on issuers before the actual rating change.

Figure 1: Rating Gap Distribution by Model



Source: Moody's Analytics

The Market Implied Ratings platform was launched in 2002 as an internal tool for Moody's ratings analysts to ensure that they have access to relevant information about the markets' views of an issuer's creditworthiness. Moody's operates on the principle of transparency in the ratings process: to the degree possible, users of ratings should have access to the same or similar information and tools as the analysts. In this spirit, Market Implied Ratings were made available to the public in 2003.

Market Implied Ratings' broad applicability has attracted many types of clients, ranging from banks, corporates, and insurance company credit departments to trading desks and hedge funds. The aim of this guide is to serve our users by describing the Market Implied Ratings platform, datasets, and methodologies.

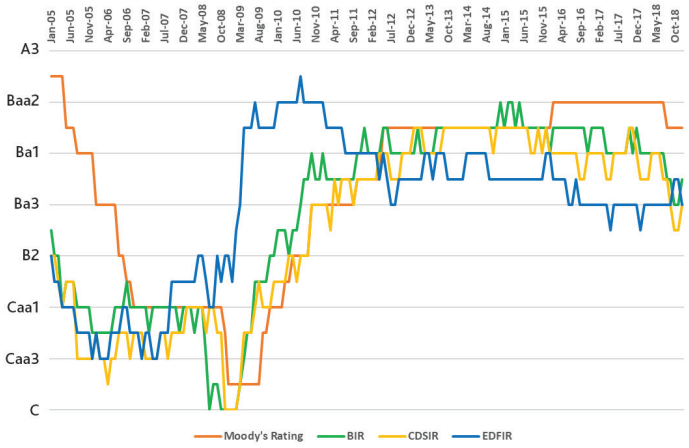
II. Overview and Background

Market Implied Ratings is a straightforward product. For over 4,000 entities it collects signals from three different market sources, the bond, credit default swap, and equity markets, and converts them to Moody's rating scale. Clients can access Market Implied Ratings data in several ways. They can visit the issuer pages on moodys.com (the source of Figure 2), receive direct data feeds, or install an Excel add-in to link their spreadsheets to the MIR database.

1 Sun and Choi (2010)

Figure 2 shows an example of Market Implied Ratings data for Ford Motor Company. It demonstrates how gaps between Moody's ratings and the various implied ratings open up, and then close, over time. In the case of Ford, the markets' views, as implied by all three signals, were more pessimistic than Moody's before Moody's rating converged with the lower market trading levels at the end of 2006. Between mid-2009 and early 2012, the markets took more positive views of Ford, ahead of Moody's again. Before the most recent downgrade in August 2018, all three markets had been priced in more risks for the company, resulting in negative rating gaps.

Figure 2: Ford's MIR



Source: Moody's Analytics

The Reference Rating

A comparison of an issuer's markets-based risk signals to its Moody's rating lies at the heart of Market Implied Ratings. This gives rise to the need to use a consistent Moody's rating for all issuers. The challenge is that many entities have a variety of ratings, reflecting the complexities of their corporate structures and balance sheets, as well as bond issue-specific factors. The Market Implied Ratings platform uses issuers' senior unsecured ratings as its common Moody's rating. However, in many cases issuers don't have senior unsecured ratings. For them, we take the equivalent ratings as generated by the Moody's senior ratings algorithm (SRA). Appendix A provides a description of the SRA.

Note that Moody's does not designate a primary rating for each issuer. For investment grade entities, most credit analysts will refer to the senior unsecured debt rating as the "Moody's rating". The Corporate Family Rating (CFR) serves that role for high yield debt issuers. As Appendix A explains, there are usually differences between issuers' senior unsecured or equivalent ratings and their CFRs. It also worth noting that the new SRA no longer associates guaranteed debts to guarantors, while in the old SRA, guaranteed debts were associated with both the original issuer and the guarantor.

In October 2015, Moody's Investor Services updated the Senior Rating Algorithm (SRA). There are three major changes in the updated algorithm relative to the previous iteration. First, the notching rules are determined dynamically instead of being static. Second, issuers with either deposit ratings or industrial revenue bond (IRB) ratings only – and by extension defaulters who defaulted on deposits or IRBs only – are added to the universe. Finally, the rules by which a defaulted entity can reenter a cohort are modified for the purposes of default and ratings performance statistics.[2]

Currently, we calculate historical and current MIRs based on the senior unsecured or equivalent ratings generated by the updated SRA.

The Comparative Analysis at the Heart of MIR

A key aspect of the platform is that the three market-based metrics — BIR, CDS-IR and EDF-IR — are displayed relative to an issuer's reference Moody's rating. This gives rise to the concept of positive or negative ratings gaps. For example, let's take an issuer with a Moody's rating of Baa2. Let's assume further that its 5-year CDS spread is in line with the median CDS spread for all A2 rated issuers, giving it a CDS-implied rating of A2. The difference between the issuer's A2 CDS-implied rating and its Baa2 Moody's rating

Figure 3: Moody's Ratings and Rating Values

Rating Value	Moody's Rating
1	Aaa
2	Aa1
3	Aa2
4	Aa3
5	A1
6	A2
7	A3
8	Baa1
9	Baa2
10	Baa3
11	Ba1
12	Ba2
13	Ba3
14	B1
15	B2
16	B3
17	Caa1
18	Caa2
19	Caa3
20	Ca
21	C

Source: Moody's Analytics

2 Typically, the new cohort reentry rules allow issuers to enter cohorts sooner. However, in certain cases, the new rules result in issuers coming back into cohorts later than in the old default history. For a more in-depth explanation of the changes, please see pages 16 - 21 in the Annual Default Study: Corporate Default and Recovery Rates, 1920 - 2015.

is three rating notches. Thus, in the nomenclature of MIR, the issuer's CDS-implied ratings gap is +3. Similarly, if the issuer's CDS traded in line with the median credit spread for contracts of Ba2 rated issuers, its gap would be -3. The direction of the sign comes from our convention of calculating gaps in terms of "Moody's minus the market", and the conversion of Moody's alphanumeric rating scale to a numerical ranking (Figure 3). Finally, if the company's CDS trades in line with the level suggested by its Moody's rating, then the ratings gap is zero.

Using Moody's rating scale for the disparate datasets on the MIR platform brings several advantages:

It allows a like-for-like comparison of risk and valuation signals from various models and markets.

It isolates issuer-specific changes. As we describe in the example of the Hess Corporation (page 9), a change in an issuer's market-implied rating signals an outperformance or underperformance vs. similarly rated entities. This is a key advantage, particularly during periods of high market volatility.

Moody's rating scale is widely utilized as a reference point in the corporate bond and CDS markets. Whether an issuer trades "rich" or "cheap" for its rating is a common way to think about relative value in the corporate debt markets. The use of this familiar framework by the Market Implied Rating platform makes its output intuitive for credit professionals.

A Global Comparison

Market Implied Ratings is a global product. It encompasses entities from around 120 different countries, and the distribution of implied ratings is broadly in line with the relative size of the world's capital markets (Figure 4). An entity's inclusion in the platform is essentially determined by two factors: whether it has a Moody's rating, and whether it has publicly traded bonds, CDS or shares with reliable prices.

Clients often ask us why we don't provide regional versions of Market Implied Ratings — for example, one that compares Australian issuers only to other Australian issuers, or that encompasses only euro-denominated debt. This question comes up most often in regards to the bond-implied ratings dataset. There are three reasons for calculating implied ratings only on a global scale.

Figure 4: Market Implied Rating Coverage

	MOODY'S RATINGS	BOND IMPLIED RATINGS	EDF IMPLIED RATINGS
Number of Issuers	3487	1046	2200
Investment Grade	67%	67%	52%
Speculative Grade	33%	33%	48%
Geographic Breakdown			
Asia Pacific	16%	15%	21%
Europe	27%	34%	22%
Latin America	5%	2%	5%
Middle East & Africa	2%	3%	5%
Supranational	1%	0%	0%
US & Canada	49%	46%	46%

Source: Moody's Analytics, as of September 28th, 2018

The first is that we take bond issues domiciled in seven different currencies and translate the non-US dollar ones to a dollar basis using a standard currency swap calculation (see Appendix B for details). Thus, all issue credit spreads are on a dollar basis (option-adjusted spread over the Treasury curve, to be precise). All issuers are therefore treated the same, obviating the need to compare issues in one currency to credit curves in another. Users wishing to see constituents of each implied rating category by region or industry can obtain the data through the Issuer List chart in the Interactive Chartroom on moodys.com by selecting market segment and industry, or region and domain.

The second reason is that we need a lot of data to produce robust common benchmarks. For CDS implied ratings, we calculate median implied ratings for each rating category. For bond implied ratings, we must calculate full credit term structures of 1 to 15 years in duration for each rating category. If we split the data sets into smaller subgroups, we would have insufficient data to estimate accurate median spread reference points. The same considerations prevent us from building separate curves and calculating implied ratings for industries or sub-sectors.

Finally, Moody's ratings are subject to a consistent global standard. The comparability should apply across each rating category, regardless of the issuer's domicile or the currency of denomination. In other words, a Baa rating indicates the same

relative level of creditworthiness across all Baa securities, no matter the issuer is in the US or in Asia.

We have found that the product's straightforwardness, particularly for CDS-implied ratings, is a big plus for users. They don't have to understand and agree or disagree with a lot of assumptions and calculations. However, by necessity, the EDF-implied ratings is more complicated. EDF-implied ratings are based on Moody's Analytics' EDFTM (Expected Default Frequency) metrics, which are derived from equity market data, combined with information on entities' liabilities. Therefore, as the least complex of the three, we will begin the discussion in the next section with the process of creating CDS-implied ratings.

High Volatility of Implied Ratings Compared to Moody's Ratings

Users often wonder about the volatility of implied ratings, especially compared to Moody's ratings. As might be expected (and as we noted in the Introduction), implied ratings are much more volatile than Moody's ratings. Among other considerations, this can be seen as a trade-off for implied ratings' better default risk identification powers, at least over relatively short time horizons.[3] Figure 5 shows the percentage of Moody's issuer ratings and bond-implied ratings which change each year.

Figure 5: Average Rate of 1-year Rating Actions, 2015Q4-2018Q3

	MOODY'S RATINGS	BOND IMPLIED RATINGS
Entities with Any Rating Action	32.1%	65.8%
Entities with Large Rating Action*	1.3%	8.2%

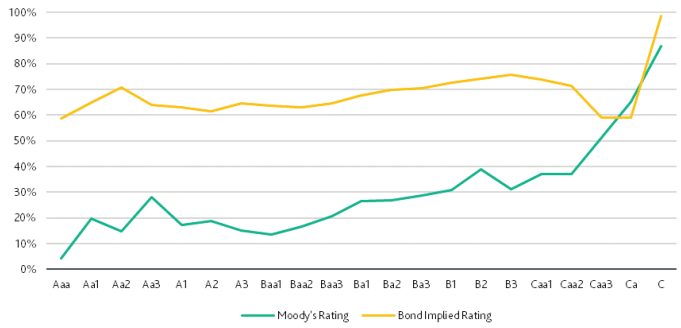
*Changes of 3 notches or more

Source: Moody's Analytics

The annual frequency of implied ratings changes for bond-implied ratings is 65.8%, while the change in actual Moody's ratings is only 32.1%. Furthermore, large ratings changes are also much more frequent for implied ratings than for Moody's ratings. When Moody's ratings change, it's relatively rare that they change more than once a year. By contrast, as the Ford example in Figure 2 indicates, implied ratings usually change multiple times over a 12-month period. Figure 6 provides an interesting contrast in the volatility patterns between Moody's ratings and bond-implied ratings.

Generally, the lower the Moody's rating, the more likely it is to change. On the other hand, the rate of change for implied ratings rises only modestly, except for Caa-C ratings.[4] We can conclude from Figure 6 that while it takes a smaller spread movement to cause a change in an investment grade implied rating, this consideration is more than offset by a lower level of spread volatility.

Figure 6: Moody's Rating and Bond-Implied 1-year Rating Change Rates by Moody's Rating Category, 2015Q4-2018Q3



Source: Moody's Analytics

III. Market Implied Ratings Datasets and Methodology

In this section we cover the three datasets contained in the Market Implied Ratings product: bond-implied ratings, CDS-implied ratings, and EDF-implied ratings.

CDS-implied Ratings

CDS Spreads Data

Our CDS price source is Credit Market Analysis Limited (CMA). The CDS spreads provided by CMA are quoted separately for each entity by currency, doc clause, tier and tenor. While a reference entity often has multiple types of CDS contracts outstanding, reflecting different currencies and documentation standards, usually one contract type dominates. It is similarly easy to separate senior from subordinated contracts.[5] And most trading takes place in 5-year maturity contracts. Thus for each reference entity, our product uses the spread on the senior 5-year contract.

We only see minimal differences in spreads across different

3 Sun and Choi (2010)
4 The ratings change rate in Figure 6 is calculated on a weekly cohort basis. That is, a rating is counted as changed if it is different at the end of 52-week period than at the beginning. So if it fluctuates during the year but ends up where it started, it is counted as unchanged. The ratings change rate for the bond-implied ratings dataset is therefore undercounted.
5 These arise with entities, usually banks that have contracts of reference securities with different degrees of subordination.

currencies, so our policy is to give priority to US dollar denominated CDS spreads, followed by euro, sterling and yen. The doc clause determines the types of default events that trigger payment. Currently, there are four main doc clauses: No Restructuring(XR), Modified Modified Restructuring(MMR), Modified Restructuring(MR) and Full Restructuring(CR). Moody's CDS-implied Ratings only take CDS spreads with the two most common restructuring types, XR and MMR, and gives priority to spreads with XR as its doc clause.

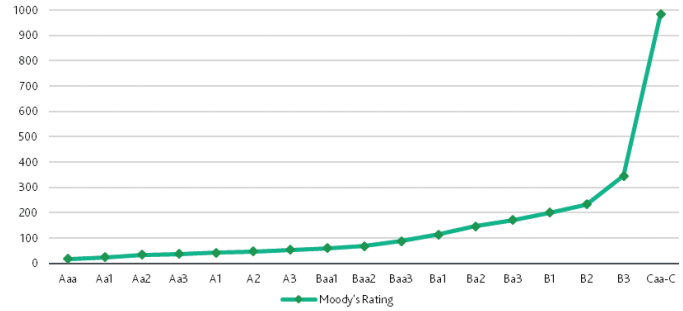
Calculating Median Credit Curves for CDS-implied Ratings

CDS-implied ratings are a relatively simple metric, and they are updated daily. In order to assign spreads to the fine rating categories, we first need to create the benchmark median CDS credit curves. Such benchmark credit curves have to be monotonic by rating class, so that we can assign ratings properly to entities based on their CDS spread

To achieve this goal, firstly, we organize the spreads by the entities' senior unsecured or equivalent ratings, and calculate the medians for each rating class on any given day. Secondly, we form a sample with the calculated median credit spreads of the mid-notch rating classes. In other words, only median credit spreads for ratings Aa2, A2, Baa2, Ba2, B2, Caa2 are included in the sample. Thirdly, we establish a log linear relationship with the sample spreads and ratings, and use the fit line to forecast the median spreads for Aaa, Ca and C rating classes. Finally, we calculate the median spreads for other rating classes by interpolation.

The above process ensures that the median spreads are rank ordered by their ratings, e.g. the median spread for Aa2 rating category is always wider then Aa1 rating category. To illustrate this phenomenon, if we were to plot CDS median spreads by rating category, the resulting curve would always be upward sloping, i.e., the median spreads rise as you move down the credit scale (Figure 7). In the interests of transparency, we make the median credit spreads available through various outlets.[6]

Figure 7: Median CDS Spreads by Rating Category



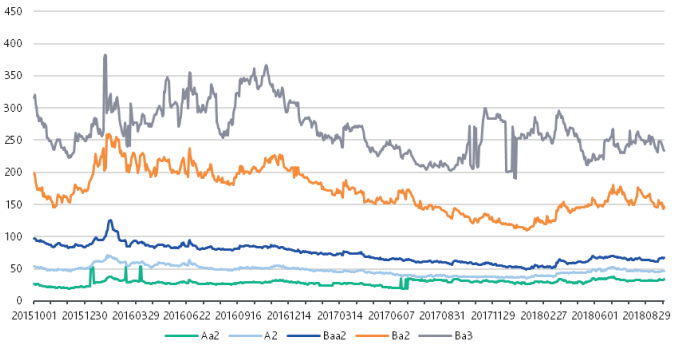
Source: Moody's Analytics, as of Sep.28th, 2018

Calculating CDS-implied ratings

Once we have established the median CDS spreads, assigning CDS-implied ratings becomes a relatively simple exercise. Each entity in the CDS-IR universe is assigned a rating value corresponding to the closest median CDS spread.

Our median CDS spreads are updated daily. Figure 7 shows representative CDS spreads over time, as available on moodys.com.

Figure 8: Median CDS Spread by Rating Category, Oct. 2015 – Sep. 2018, bps

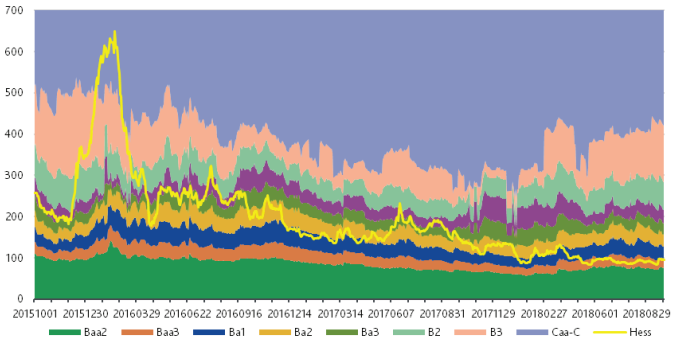


Source: Moody's Analytics

A final note concerns the boundaries between each implied rating category. Most issuers do not sit exactly on a median credit spread value. Rather, they end up somewhere between them, and thus receive corresponding fractional values. As can be seen from the Hess Corporation example below (Figure 9), CDS that falls in a certain range around a median credit spread receive the implied rating associated with that spread. We determine the boundary between the rating categories by taking the geometric mean of the two neighboring spreads.[7]

6 Median credit spreads are available on Moodys.com, Moody's Excel Add-in, and by File Transfer Protocol
7 The geometric mean is the square root of the product of the two spreads.

Figure 9: Relationship between Hess Corporation's CDS Spreads and its CDS-implied Ratings



Source: Moody's Analytics

Figure 9 clearly illustrates the dynamics of implied rating changes. The colored areas outline the value range of the spreads to which CDS-implied ratings are assigned. From December 1st, 2015 to February 19th, 2016, the CDS implied rating for Hess dropped four notches from Ba3 to Caa1, which represents a 467 bps move in the CDS spread. However, from February 20th, to April 18th, 2016, Hess' CDS-implied rating reverted back to Ba3 with only a 411 bps decrease. In other words, Hess' CDS-implied rating reflects the relative, not absolute, difference of changes in its spread versus shifts in the broad market.

Bond-implied Ratings

Working with bonds is much more labor-intensive than CDS, and CDS are generally considered to provide more accurate signals of credit risk. So what do we gain by including the bond dataset in the Market Implied Ratings platform? The bond dataset's longer price history provides one major advantage. Having data back to 1999, a period which includes another cycle of credit busts and booms, significantly strengthens our research results. By contrast, the CDS data is only available from 2002 on a monthly basis. We began producing daily CDS implied ratings in 2004.

A second point is that the inclusion of the bond dataset allows MIR subscribers to use the data to analyze arbitrage opportunities across different markets.

Finally, the bond dataset includes issue and issuer-level implied ratings and other information, all of which is available to subscribers. Figure 10 shows a screen grab of issue-level information for a sample entity. Such data allows subscribers to use MIR to analyze issue-specific curve trades.

There are three major steps in determining an issuer's bond-implied rating. First, we form a bond-implied ratings dataset with certain criteria, and calculate bond spreads and durations. Next, we calculate issue-level bond-implied ratings and issue-level bond-implied rating gaps. Last, we aggregate the issue-level bond implied rating gaps to generate the issuer-level bond implied ratings.

Figure 10: Hess Corporation's MIR Debt List

ISIN	COMPANY NAME	CURRENCY	ISSUED AMOUNT (MIL)	MATURITY DATE	COUPON	MOODY'S RATING	BOND IMPLIED RATING	BOND IMPLIED RATING GAP
US42809HAF47	HESS CORP	USD	300	15-Jul-24	3.5	Ba1	Baa3	1
US42809HAG20	HESS CORP	USD	1000	1-Apr-27	4.3	Ba1	Baa3	0
US023551AF16	HESS CORP	USD	700	1-Oct-29	7.875	Ba1	Ba1	0
US023551AJ38	HESS CORP	USD	750	15-Aug-31	7.3	Ba1	Ba1	0
US023551AM66	HESS CORP	USD	600	15-Mar-33	7.125	Ba1	Ba1	0
US42809HAC16	HESS CORP	USD	750	15-Jan-40	6	Ba1	Ba1	0
US42809HAD98	HESS CORP	USD	1250	15-Feb-41	5.6	Ba1	Ba1	0
US42809HAH03	HESS CORP	USD	500	1-Apr-47	5.8	Ba1	Baa3	1
Issuer Level						Ba1	Ba1	0

Source: Moody's Analytics, as of September 28, 2018

Building the Bond-implied Ratings Dataset and Calculating Bond Spreads

We start with a daily feed from our vendors of bond prices, spreads, and indicative information such as issuer name, issue identifier, maturity, and coupon. The incoming prices are matched against the Moody's ratings database, which holds the bond issues rated by Moody's. All the issues that meet a list of criteria (see the sidebar titled Bond Inclusion Criteria on this page) then go in the product. As many readers will recognize, this is much like the process of constructing a bond index. We begin with information on over 100,000 rated bonds. Of these, pricing information is available for around 40,000 issues. Ultimately, around 16,200 issues pass through the inclusion criteria to make up the bond-implied ratings dataset.

We calculate our daily prices and option-adjusted spreads from a blend of Reuters, MarketAxess (for European bond market data), and TRACE data. The general rule is that the more recent the traded price and the larger the transaction, the more reliable it is. The algorithm was developed by determining the balance among the three sources that best "predicted" the next price movement — with the benefit of hindsight, of course. We also subject our vendor prices to a quality assurance process. This includes the elimination of bonds that are subject to tender offers, since their trading levels do not reflect the market's view of the issuers' creditworthiness. Therefore, we make available our quality indicator, which uses an algorithm based on several factors that include the reliability of the vendor, the quality or depth of the price or spread, and the amount of the issue.

Determining the credit spread for bonds with put and call options is a more complex exercise. We discuss these and other credit curve-building issues in Appendix C.

Calculating Issue-level Bond-implied Ratings

Once we have established the list of eligible bonds and their spreads, the next step is to calculate the issue-level bond-implied ratings. Our algorithm creates a composite spread from the prices supplied by our data venders. Based on the composite spread, the duration of each bond, and the bond's rating, the algorithm assigns a number representing an issue-level bond-implied rating gap. Calculation details are also discussed in Appendix C.

BOND INCLUSION CRITERIA

In order to be included in the bond-implied rating dataset, an issue must meet the following criteria:

- Rated by Moody's
- Denominated in US dollars, euros, sterling, yen, Swiss francs, Canadian dollars, or Australian dollars
- Have a duration of at least one year
- Have a fixed coupon
- Have a minimum face value of US$100 million or the equivalent
- Have a price of at least 40
- Have a maximum of four coupon payments p.a.
- Not have a sinking fund feature
- Not convertible to equities
- Have a coupon greater than 0% but less than 30%
- Be direct obligations of industrial, financial, utility, sovereign, or sub-sovereign entities. That is, not be structured in nature
- Not linked to an index (e.g., inflation-linked)
- Not covered by assets (e.g. covered bond)
- The debt can have callable or puttable features, as long as the next call or put date is at least one year away.

Calculating issuer-level bond-implied ratings

We then determine the issuer-level bond-implied ratings by averaging the issue-level implied rating gaps from each entity's list of bonds. 42% of all the issuers under coverage have only one actively traded bond, based on the data on September 28, 2018, while 21% of issuers have more than 5 bonds with trading prices. The weight we place on the issue-level implied rating is determined by the issue's face amount, age, duration, seniority, coupon frequency etc.

A related question is how we account for issues from the same entity but which have different Moody's ratings, e.g., because some are senior and others are subordinated. We address this by calculating each issue's gap vs. its assigned Moody's rating, and

then averaging the gaps. The average gap is then set relative to the senior unsecured or equivalent rating assigned to the issuer.[8] This last step provides the bond-implied ratings gap.

An example might help explain the process. Let's take an issuer with a Moody's senior unsecured or equivalent rating of Baa1. It has two bonds outstanding, one senior and one subordinated. The senior bond has a market-implied rating of Baa1 and thus a bond-implied ratings gap of 0. The subordinated issue has a Moody's rating of Baa2 and a gap of -2. Both issues are of the same size and approximately the same duration, so they are weighted equally in calculating the issuer-level bond-implied rating gap. This would be -1, i.e., the simple average of the issue-level gaps of 0 and -2. The issuer-level gap of -1 would be set in relation to the senior unsecured or equivalent rating of Baa1 to give an issuer-level bond-implied rating of Baa2.

EDF-implied Ratings

For bond- and CDS-implied ratings, the level of an issuer's credit spread serves as a good proxy for the market's view of its credit risk on a forward-looking basis. Similarly, the value of the firm's equity as measured by market capitalization provides insight regarding the default risk of the firm. But market capitalization is far from a direct measure of default risk: for example, firms with strong growth prospects, and thus high share prices, can also have elevated levels of default risk. Thus, another approach must be taken to extract credit risk signals from equity market data.

One response to this problem is to employ the so-called Merton contingent claims approach to modeling default risk from companies' share prices and information from their capital structures. The Merton framework has been substantially refined by Moody's Analytics to produce its widely used Expected Default Frequency (EDF™) metrics.[9] EDF metrics are mapped to Moody's rating scale in the process described below to produce EDF-implied ratings.

How are EDF values mapped to Moody's rating scale?

The mapping from EDF measures to implied ratings is determined by calculating median EDF measures per rating category by using a "spot median" methodology. The spot median for a major rating category captures the median of the most recent month's EDF values for all global entities that fall into this rating class.

Figure 11: Scheme to Compute Median EDF Credit Measure for Major Rating Classes

MAJOR RATING	MEDIAN EDF (NOTATION)	MEDIAN EDF COMPUTATION
Aaa	MAaa	Median across firms with rating Aaa
Aa	MAa	Median across firms with ratings Aa1, Aa2, or Aa3
A	MA	Median across firms with ratings A1, A2, or A3
Baa	MBaa	Median across firms with rating Baa1, Baa2, or Baa3
Ba	MBa	Median across firms with rating Ba1, Ba2, or Ba3
B	MB	Median across firms with rating B1, B2, or B3
Caa	MCaa	Median across firms with rating Caa1, Caa2 or Caa3. When the number of firms in this class is less than 25, an adjustment based on MB is used.
Ca	MCa	Geometric mean of MCaa and 50%
C	MC	50%

Source: Moody's Analytics

The approach used to obtain the spot median EDF measure for a major rating class is summarized in Figure 10. There are dispersions of EDF measures by rating category, just as there are dispersions of bond and CDS spreads by grade that reflect market perceptions of risk differences within each category. If there are very few firms in a rating category, the median EDF will move around more, due to change in single-firm EDF metrics.

A lower, or riskier, agency rating generally corresponds to a higher median EDF value. However, market-based measures do not reveal a consistent risk difference between fine rating categories. That is, on any given day, A3 firms may have a lower median EDF measure than A2 firms. This is particularly true for high-quality firms in fine rating grades where median EDF metrics per rating category are only a few basis points apart from each other. Due to the need to preserve monotonicity, we use the broader data on major rating categories to set the bands, then map fine grades between these by a geometric means approach, as explained below. This exercise is repeated

8 Please see Appendix A for a description of how we determine an issuer's senior unsecured or equivalent rating.
9 An explanation of MKMV's methodology is beyond the scope of this paper. For details, please see Crosbie and Bohn (2003). Dwyer and Qu (2007) provides an overview of enhancements to the model. Crossen, Qu, and Zhang (2011) provides recent validation results.

at the end of each month. It should be noted that we set the mapping to very low-quality grades as constant. Specifically, we map Ca credits to the geometric mean of the Caa EDF level and an EDF metric of 50%, and we map C to 50%. Setting constants to low-grade categories is due to the limited number of firms in such categories, and calibrating the medians month by month yields volatile mappings. The constants used are calibrated from a long-term pooled sample.

The fine rating classes are based on the weighted geometric mean of the neighboring major rating categories. The median EDF metric should rise at an increasing rate as the ratings deteriorate, i.e., the median EDF metric should be a convex function of the ratings. For example, if a median EDF metric for Baa2 is 20 bp and a median EDF metric for Ba2 is 50 bp, then a rating in between the two should be closer to 20 bp than 50 bp. This is because the default rate rises in a convex manner as the ratings deteriorate.

To ensure this, if two medians are too close, we impose a minimum, median EDF distance between those major neighbors. Specifically, the lower or more risky neighbor of a major rating category will have a median EDF value that is, at least, a multiple of 2 from said major category. Note, the median EDF value for Baa is never adjusted, because it acts as the absolute reference. For example, suppose the EDF medians of the major rating categories Baa and its neighbor Ba are 0.50% and 0.65%, respectively. Since the distance between these two medians is not at least a multiple of 2, we reset the median EDF value of Ba to 1% since 0.50% x 2 = 1%.

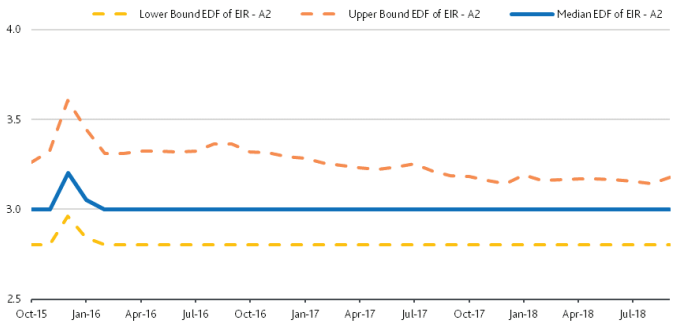
After calculating median EDF measures, the EDF range within a grade is computed from the median EDF of two adjacent rating grades. The EDF range is simply the geometric mean of the two median EDF values. For example, if we want to compute the EDF range of the Aa grade and if the median EDF measures for entities rated Aa1, Aa and Aa3 are 0.02, 0.03 and 0.04 respectively, the EDF range of the AA grade should be computed as follows:

$$Lower\ bound\ of\ \ Aa\sqrt{0.02\times.03}=0.024$$

$$Upper\ bound\ of\ \ Aa\sqrt{0.03\times.04}=0.035$$

So, the EDF range for the Aa grade would be 0.024 ~ 0.035 in this example. This methodology is consistent with our earlier approach of interpolating between major categories, using geometric means for finer categories.

Figure 12: EDF Range for Corporate Issuers with an EDF-Implied Rating of A2



Source: Moody's Analytics

Once we have the EDF ranges for each category, we are able to assign an EDF-implied rating for a given EDF value. As shown in Figure 11, the median EDF value for each credit category does not vary much over time. Since January 2016, the median EDF for A2 has stayed consistently at 3 bps. However, the EDF range covered in the finer rating buckets has not.

Therefore, knowledge of the EDF-implied credit category does not give an exact picture of the default risk level. This also means that there can be significant variation in default risk levels across time within the same EDF-implied rating category.

Update to the EDF-implied rating methodology with the release of EDF9

The EDF-implied rating methodology was updated in May 2015, along with the release of the ninth generation EDF model, EDF9. The purpose in updating the methodology is to make implied ratings more consistently interpretable while maintaining their intuitiveness.

There are a few improvements to the existing approach. Most significantly has been the creation of separate distributions for financials and non-financial corporates. In addition, the median calculations have been updated for improved accuracy, and the mapping is now based on a global set of rated entities whereas the original EDF-Implied Rating used only rated North American corporates as the reference distribution.

A more in depth analysis of the differences between the two models as it applies to financial firms can be found on the research section of moodys.com.[10]

10 https://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_1006101

Appendix A – Moody's Estimated Senior Unsecured Ratings

For a variety of purposes, it is desirable to compare Moody's ratings of different issuers across a single class of debt in order to abstract from differences in ratings that may reflect security-specific differences in seniority or security rather than differences in an issuer's fundamental credit risk. This is essential because conducting rating performance statistics at the issuer level requires a common basis of comparison. Moody's uses the Senior Ratings Algorithm (SRA) to derive senior unsecured issuer-level ratings from various ratings assigned at the instrument-level and the issuer-level, and we call the resulting output estimated senior unsecured ratings or estimated senior ratings.

Briefly, a company's estimated senior rating is set equal to its actual senior unsecured debt rating if one is outstanding. If the company does not have any senior unsecured ratings, the SRA estimates its senior rating on the basis of other outstanding instrument-level or issuer-level ratings.

The estimated rating that results from this process is not equivalent to an actual Moody's senior unsecured credit rating, which benefits from the careful deliberations of the rating committee process. The method of estimation is, however, designed to ensure that the derived ratings are consistent with Moody's notching practices, and therefore theoretically equivalent to a senior unsecured bond rating.

An issuer's estimated senior unsecured rating is a key component of the Market Implied Ratings product. Determining the rating would seem to be a straightforward process. Unfortunately, it is not. Mainly, it is complicated by the complexities of many issuers' capital structures and the varying characteristics of bond issues.

The Senior Ratings Algorithm (SRA)

The Senior Ratings Algorithm (SRA) lies at the heart of the process of determining an issuer's estimated senior unsecured rating.[11] Moody's updated the algorithm in late 2015. The new SRA operates as a three-step process for a given issuer. In the first step, notching rules are created based on the average notch difference in ratings between each class of debt and the senior unsecured debt of an entity.[12] In the second step, the entity's reference credit—the debt class rating that has the highest priority—is selected. This is accomplished by ranking each class of rating on the basis of its ability to predict the senior rating; this ranking is referred to as the priority of the notching rule. In the third step, the reference credit's rating is adjusted by the number of notches based on its corresponding notching rule to estimate the entity's senior rating.

In October 2015, Moody's began to publish default and ratings performance studies on corporate issuers utilizing an updated SRA. There are three major changes in the updated algorithm relative to the previous iteration. First, the notching rules are now determined dynamically instead of being static. Second, we allow issuers with either deposit ratings or industrial revenue bond (IRB) ratings only – and by extension defaulters who defaulted on deposits or IRBs only – to enter the universe. Finally, we have modified the rules by which a defaulted entity can reenter a cohort for the purposes of default and ratings performance statistics.

The current version of MIR incorporates the updated estimated senior unsecured ratings.

Eligible Obligor and Reference Rating Selection

We first tackle the identification of eligible obligors and their reference ratings. The set of obligors eligible for a senior rating roughly consists of all corporate and sovereign issuers of Moody's-rated long-term public, Rule 144A debt, and syndicated bank loans. Obligors with only enterprise level ratings, such as corporate family ratings, and no rated debt of their own are generally excluded. The SRA also excludes public finance (municipals) and sub-sovereign entities, government-sponsored enterprises, and certain sovereign-guaranteed and sovereign-related entities. Since the purpose of the SRA is to generate issuer-level ratings, debt obligations that do not reflect the fundamental default risk of the obligor, such as structured finance transactions and short-term debt, need to be removed. It is worth noting that industrial revenue bonds, which were excluded in the previous version of the SRA credit universe, are now incorporated in the redesigned SRA. The new SRA no longer associates guaranteed debts to guarantors, while in the old SRA, guaranteed debts were associated with both the original issuer and the guarantor.

11 For details on the SRA methodology, see Gupta and Parwani (February 2009).

12 The term "notching" is used by rating agencies to refer to the practice of adjusting ratings to account for factors such as the seniority and security of the obligations. (For the uninitiated, a "notch" is a rating level – so the difference between A2 and A3 is one notch.) A common use of notching is to make expected loss distinctions across the hierarchical debt classes within an issuer's capital structure.

Each credit from among this broad universe is characterized along the following dimensions:

- Class of debt or entity-level rating (e.g., regular bond, bank loan, first mortgage bond, Issuer Rating, Corporate Family Rating)[13]
- Seniority (e.g., senior unsecured, senior secured, subordinated)
- Backing status (not backed, internally backed, externally backed)
- Currency type (e.g., local currency, foreign currency)

The four dimensions listed above are the salient factors affecting a particular credit's rating in relation to other credits in an entity's capital structure. We expect that for a given entity, credits that match along these four dimensions (referred to as credit groups) are homogenous and share the same rating at a fixed moment in time. In cases where ratings from the same credit group differ for a given entity, we calculate the median rating at each point in time.[14] In this way, we construct sanitized credit rating histories for each entity and refer to them as aggregated credit group histories.

The SRA aims to estimate the hypothetical senior unsecured, non-backed, local currency, regular bond rating—in other words, the benchmark rating—for each entity. For entities that already have a benchmark rating, no estimation is required.

Dynamic Notching Rule

Once we compute the aggregated credit group histories, we infer notching rules from each credit group to the benchmark rating. A notching rule is an abstraction for the prevailing notch difference that exists between a given credit group rating and the benchmark rating of the same entity as a function of time, credit group rating level, region and sector.[15]

For each credit group and among the set of entities that have both the credit group rating and the benchmark rating, we compute the most frequently observed notch difference as a function of time, the credit group's rating and the entity's region and sector. If there is not sufficient consensus for a particular rule, no rule can be formed.[16] Rather than relying on static notching rules as the previous SRA did, the redesigned SRA allows historical ratings to drive the formation of notching rules, which can evolve over time.

Having inferred notching rules, we then select the reference credit group for each entity at all points in time. The reference credit group is the one whose notching rule most reliably predicts the benchmark rating. In other words, it is the credit group that has the highest priority. A notching rule's priority is broadly based on two factors:

- How consistent is the credit group's notching from the benchmark rating?
- How targeted is the pool of entities from which the notching rule was formed? The more consistent a credit group's notching is, the higher priority it will be assigned. For two notching rules that are equally consistent, the rule that is formed from a more targeted pool of entities (with respect to the entities for which we are selecting the reference credit group) will be assigned a higher priority.[17]

We have revised how we choose the reference credit group for entities that selectively default on subordinated debt, but continue to pay on senior debt obligations. The previous SRA chose the defaulted subordinated debt as the reference credit group when the gap between the senior and subordinated debt ratings becomes wider than historical standards. This resulted in an artificially lowered rating, and was intended to balance two competing considerations: (1) estimating entity-level ratings, assuming that default risk is shared evenly across the entity's capital structure, and (2) reflecting Moody's ratings' true discriminatory power by referencing the subordinated debt rating. In the redesigned SRA, we make no such adjustment for selective defaults.[18]

Once we have determined the reference credit group for a particular entity, we apply its notching rule to the reference credit group's rating to derive the estimated senior rating. In this way, we construct entity-level estimated senior rating histories at all points in time.

13 Moody's Rating Symbols and Definitions (November 2018) provides detailed definitions for Issuer Ratings and Corporate Family Ratings.
14 If there are an even number of credits in the credit group, we select the worse rating among the two middlemost ratings. We refer to this as the Median-Worst algorithm.
15 Even though we refer to "notching rules", in no way are we suggesting that Moody's rating analysts rigidly follow these rules in practice. Our algorithm only seeks to determine the "average" notching observed within a particular region and sector.
16 In order for a rule to be formed, we require two conditions be satisfied: (1) at least 50% of all entities must have the same notching, and (2) there must be at least 10 entities that have the same notching.
17 For ease of exposition, this discussion of priority has been simplified.
18 The previous approach led to a more correct rating accuracy measurement at the expense of introducing inaccurate ratings while the new approach has the opposite effect. We plan to address this issue in the future by doing studies at the instrument level or by censoring non senior unsecured defaults when doing senior unsecured entity-level studies.

Smoothing

It is possible that an entity's estimated senior rating history created in the previous step contains artificial rating changes—that is, rating changes that are unsupported by the entity's underlying aggregated credit group histories.[19] Artificial rating changes can be introduced due to changes in the reference credit group or changes in the notching rule. To remove these artificial rating changes, we apply a remedial smoothing procedure, by which we mean the process of shifting the entity's estimated senior rating history either prior to or after an artificial rating change by the same magnitude as the intended artificial change. This has the effect of eliminating the artificial rating change at the cost of distorting the entity's rating level.

The redesigned SRA allows artificial changes in an entity's estimated senior rating history to be smoothed either back in time or into the future. If the priority of the current notching rule is higher than that of the previous notching rule (with respect to a particular artificial rating change), the entity's estimated senior rating is smoothed back in time, meaning the previous rating is replaced with the current rating. Conversely, if the priority of the current notching rule is lower than that of the previous notching rule, the entity's estimated senior rating is smoothed into the future, meaning the current rating is replaced with the previous rating.

19 Aggregated credit group histories, as defined previously, are the rating histories calculated as the Median-Worst rating among all like credits of a particular entity.

Appendix B – Currency Swap Calculation – Conversion to the US Dollar for Bonds

If exchange rates were fixed, the yield for a corporate bond seen by investors around the world should be the same. The spread over the benchmarks would differ but only because the yield on the benchmarks would vary. Unfortunately, exchange rates change continuously over time. A US-based investor has to convert each of the bond's cash flows differently using both the current exchange rate and exchange rate futures. Investors from different countries will therefore see and receive different yields from investments in the same bond issue. To calculate the yield on non-dollar bonds one uses the standard equation:

$$P_0 = \frac{100}{(1+y)^T} + \sum_t^T \frac{c}{(1+y)^t} \quad \text{(B1)}$$

In the above equation, c denotes the amount of each coupon payment, and y is the bond yield in local currency.

To calculate the yield in US dollars, one must adjust each cash flow with the appropriate forward exchange rate:

$$P_{0,USD} * S_0 = \frac{100 * F_T}{(1+y_{USD})^T} + \sum_t^T \frac{c * F_t}{(1+y_{USD})^t} \quad \text{(B2)}$$

where S_0 is the current exchange rate and F_t is appropriate forward exchange rate. To calculate the forward exchange rates, we can use interest parity with the underlying government bonds to create a synthetic currency swap.

$$\frac{F_t}{S_0} = \left(\frac{1+r_{USD,t}}{1+r_t}\right)^t \quad \text{(B3)}$$

Where $r_{USD,t}$ and r_t are the US and foreign government bond yield respecitvely. Combining the above two equations, and assuming the interest rate curves are flat, we can get the following relation:

$$1 + y_{USD} = (1 + y) * \frac{1+r_{USD}}{1+r} \quad \text{(B4)}$$

With this equation in hand, we use a common but imperfect shortcut in the bond-implied ratings dataset to convert the spread on non-US dollar bonds to a dollar basis. Instead of using the Treasure interest rate curves, we use the swap rate curves as an approximation of the average interest rate over the maturity of the bond and assume that the interest rate curves are flat. This allows us to use Equation (B4) directly. The swap rates assume an exchange of fixed cash payments and so it is only the existence of the principal payment at maturity that requires an assumption of flat interest rate term structures.

The two main advantages to this method are:

- It allows us to use the relatively more reliable swap rate quotes instead of interest rate quotes
- The approximation works as well for callable and other non-standard bonds as it does for bullet bonds.

The main drawback is that there is a small bias incurred due to differences in the interest rate term structures. Specifically, if the dollar interest curve is rising faster (slower) with maturity than the non-dollar curve, our estimate will be slightly low (high). This bias has typically been a few basis points at most.

Appendix C – Calculation of Option-Adjusted Spreads, Bond-implied Rating Median Credit Spreads, and Credit Curve Construction

Calculating Option-adjusted Spreads

Approximately 35% percent of the bonds used for MIR have embedded options (such as calls). The market uses two methods for estimating the credit risk of these bonds that removes the influence of embedded options on the yields. One is to use a spread for a hypothetical bond where the option has been removed —the option-adjusted spread (OAS). It is measured by the current spread over the benchmark curve minus that component of the spread that is attributable to the cost of the embedded options.

The other is to assume the bond will be called at the worst possible time for the debt investor in terms of total return — the spread to worst. We use a weighted average of the two methods in an effort to follow market standards. Several sources state that bonds are likely to be called if their yield to maturity is less than available market yields. We formalize this with the following rules: If the dirty price of the bond is $102 or greater, spread-to-worst is used. If it is $98 or less, the option-adjusted spread is used. A smooth, linear transition is used for values in between. The smooth transition is intended to avoid jumps in the market implied ratings not due to truly discrete changes in the bonds' risk profiles.

Calculating Median Credit Spreads

The median MIR credit spreads are intended to represent the spread on a typical bond at a company not experiencing a current credit-related event. The first step, then, is to limit the data set to bonds of issuers who are not on Moody's Watchlist. Because bonds in the Asian-Pacific rim countries appear to be priced much higher than expected given their credit risk and comprise a small portion of the data set overall, bonds from these countries and bonds denominated in yen and Australian dollars are also removed during the calculation of median spreads.

After filtering, each issue is sorted into broad rating categories, or buckets. The board rating categories are Aaa, Aa, A, Baa, Ba, B1, B2, B3, Caa1, and Caa2 and below. Prior to June 2004, B1, B2, and B3 are collapsed into the broad B category and Caa1 is absorbed by the Caa2 and below category (Aaa, Aa, A, Baa, Ba, B, Caa and below).

For each group, we calculate the median credit spread curves in two steps: first by calculating medians by rating and duration, and second by the fitting of power curves.[20] The medians focus the results on representative (median) observations, while the curve-fitting process smooths the output.[21]

For each bucket, we sort the data set by duration. The sorted data set for each broad rating category is then grouped into overlapping batches of 21 consecutive observations. We select a 'median' duration (the 11th duration in the batch), and a modified 'median' spread from each of these batches. The durations and spreads so obtained are then used as the data points for constructing the spread curves. For broad rating category Ca/C or any broad rating category with less than 21 bond data, we include all duration/spread data in this broad rating category into the sample.

A potential problem in choosing the simple median spreads in the batches of 21 observations is that the median spread of a batch, instead of being representative of the broad rating category, could be biased towards one of the finer rating categories. For example, it is clear that the median spreads for broad Aa category in a batch should be close to the median spreads for Aa2 category. However, when we combine the fine spreads data into one data set, it is possible that most of the spreads in the batch for the broad Aa category actually belong to the fine Aa1 category. Thus, choosing a simple median spread from this batch is likely to yield a spread that is narrower than the 'real' median Aa spread since the simple median spread is actually representative of the Aa1 category rather than Aa2. We solve this problem by choosing not the simple median spread but a modified median spread from a given batch of 21 observations as the median spread for the batch. The idea is that if the mix of observations in a batch is biased towards a fine rating category then the spread we select as the 'median' should be biased, and we need to modify the 'median' spread to cancel such bias.

For illustration, in the previous example, since the simple Aa1 median spread is likely to be smaller than the simple median Aa2 spread, therefore, we choose a spread higher than the median Aa1 spread as the true median spread for Aa2. The

20 We use duration instead of maturity because we have noted an empirical relationship between coupon rate and spread. Bonds with larger coupon rates are found to have larger spreads, even in cases where everything else is the same including issuer and maturity. We inferred that the extra spread was due to the higher exposure to interest rate risk, not higher exposure to credit risk.

21 The smoothing is similar to spline methods and the Nelson-Siegal methods.

spread we choose as the modified median spread is the *dth* spread in the sorted batch of 21 observations where

$$d = n1 + int(n2/2) \quad \text{(C1)}$$

and n1 is the number of spreads in Aa1 category, and n2 is the number of spreads in the Aa2 category. This formula pushes the value of d closer to 21 (and, therefore, pushes the corresponding spread higher) whenever there are more spreads belonging to Aa1 compared to the other categories. Similarly, it pulls the median spread lower if there are more observations in Aa3 category.

Constructing and Refining Median Credit Spread (MCS) Curves

Once the duration and the corresponding spreads have been obtained, we fit the following curve with the data of each broad rating category:

$$Spread = \beta * Duration^{\alpha} \quad \text{(D1)}$$

The above power curve has two degrees of freedom, and provide upward and downward sloping curves. It does not allow for humps in the spread term structure, but we have not found humped behavior in our spread series, probably because we focus on durations greater than one year.

This equation can be linearized and estimated using ordinary least squares in the following form:

$$\ln(Spread) = \ln(\beta) + \alpha * \ln(Duration) \quad \text{(D2)}$$

The process starts with the Aa rating category because the Aaa category typically has very few observations. The Aaa category is then calculated and restricted to fall below the Aa rating category. After that, the other rating categories are estimated in sequence moving down the rating scale. If the curve does not overlap with the preceding curve, no adjustments are made. If the curve crosses the preceding curve moving downwards prior to a 15-year duration, the curve is constrained to cross at 15 years while still minimizing the sum of squared errors. If the curve crosses the preceding curve moving upwards, Ln(β) is constrained to be a certain distance higher than that of the previous curve and α is adjusted to minimize the sum of squared errors. These constraints to prevent curves crossing are necessary for the proper function of the product.

Median credit spreads by maturity are calculated by assuming that the median spreads by duration were created using bonds priced at par. Combining the equations for par coupon bonds and that for calculating yields leads to a numerically calculable solution.

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