Credit Strategy Group

**David W. Munves, CFA**
tel: 1 212 553-2844
david.munves@moodys.com

**David T. Hamilton, Ph.D.**
tel: 1 212 553-1695
david.hamilton@moodys.com

Credit Policy Group

**Christopher Mann, PhD**
tel: 1 212 553-7102
christopher.mann@moodys.com

**Matthew Woolley**
tel: 1 212 553-4508
matthew.woolley@moodys.com

Moody's KMV

**Doug Dwyer**
tel: 1 212 822-2821
douglas.dwyer@moodys.com

**John Gibbon**
tel: 1 415 874-6641
john.gibbon@moodys.com

**Shisheng Qu**
tel: 1 415 874-6243
shisheng.qu@moodys.com

Research Support

**Eugenia Fingerman**
tel: 1 212 553-4181
eugenia.fingerman@moodys.com

Product Strategy

**Jonathan King**
tel: 1 212 553-1623
jonathan.king@moodys.com

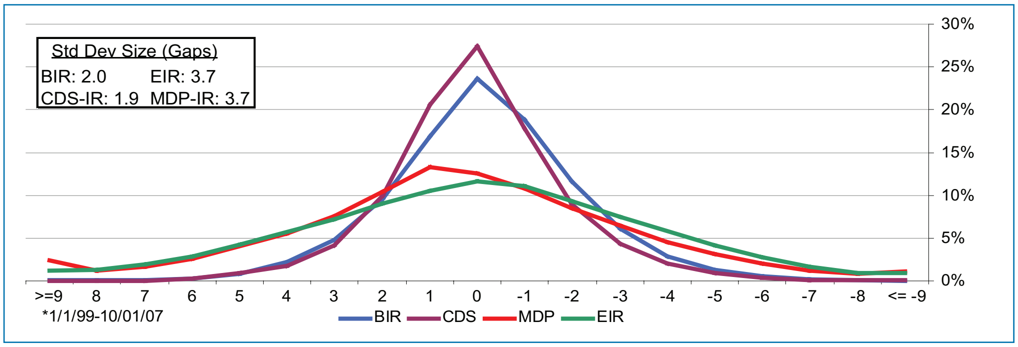
# Moody's Market Implied Ratings
## Description, Methodology, and Analytical Applications

Market Implied Ratings provides credit risk and relative value signals from five sources; Moody's ratings, the corporate bond, credit default swap (CDS) and equity markets, and company financial ratios. This guide provides users with information on Market Implied Ratings and related research, and explains how risk managers, analysts, and investors can use MIR to improve the quality and efficiency of their decision-making processes.

## Contents



### Ratings Gap Distributions by Market and Model




Moody's Investors Service

<u>*Note from the Editor:*</u>

*This guide to Market Implied Ratings and their applications was a collaborative effort among several Moody's groups, namely Credit Strategy, Credit Policy, and Moody's KMV. Together we aimed to produce a document that is readable for general user, while providing a greater level of detail for those seeking a deeper understanding of MIR. As part of this, the guide also addresses the most frequently asked questions that have come up in our discussions with external and internal users of the product.*

*The authors would like to acknowledge the helpful comments from many colleagues, including Richard Cantor, Jonathan King, Michael Love, Robert Eckerstrom, Njundu Sanneh, Dana Gordon, and Anne Tracy.*

*We hope you will find the guide useful and informative. Please do not hesitate to contact us with any questions, comments, and suggestions for improvement.*

*David W. Munves, CFA*
*Managing Director*
*Credit Strategy Group*

# I. Introduction

**Credit ratings are just one of many opinions about an issuer's creditworthiness**

**FAQ 1: What are market-implied ratings?**

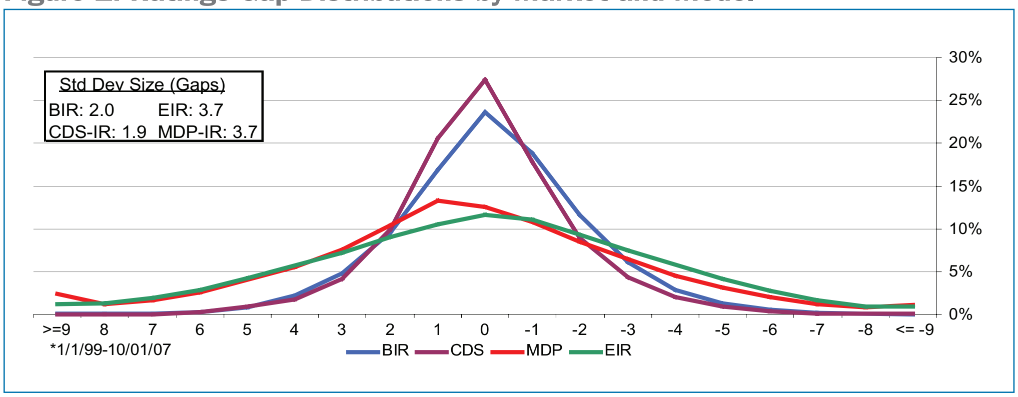
Credit ratings are just one of many opinions about an issuer's creditworthiness, and disagreements between Moody's ratings and other valuation and risk metrics have been around for a long time. Sometimes they simply reflect varying conclusions, arrived at by processes that are, by necessity, as much art as science. In other cases the differences stems from factors related to the framework of analysis. For example, Moody's takes a medium-term view and aims to "rate through the cycle", while markets tend to operate on a shorter term horizon. Such choices involve trade-offs. 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 when markets are "better", there is a cost in terms of the higher volatility of implied ratings compared to Moody's ratings.

Moody's Market Implied Ratings platform captures disagreements over time between Moody's ratings and four valuation metrics for industrial, financial, utility, sovereign, and sub-sovereign entities (Figure 1). These disagreements are usually viewed as representing differences of opinion between Moody's and the market about an issuer's creditworthiness. However, they can also reflect factors such as liquidity or investor preference.

**FAQ 2: Is MIR used by Moody's ratings analysts?**

Market Implied Ratings was launched as an internal tool for Moody's analysts in 2002, and was used to ensure that the ratings teams had access to all 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 greatest degree possible, users of ratings should have access to the same information and tools as the analysts. In this spirit, Market Implied Ratings was made available to the public in 2003.

**Figure 1: Ratings Gap Distributions by Market and Model**




The MIR data, while valuable, gave rise to many questions on the part of clients and Moody's analysts. For example, what are the implications of an issuer trading cheaply to its Moody's rating? Does this signify a greater risk of downgrade or default? Are there relative value signals hidden in the data? The Credit Strategy Group was formed in early 2005 to help answer such questions.

**Moody's Market Implied Ratings platform captures disagreements over time between Moody's ratings and four valuation metrics**

Market Implied Ratings' broad range of applications has attracted many types of clients, ranging from credit departments to trading desks and hedge funds. The aim of this guide is to serve our users by:

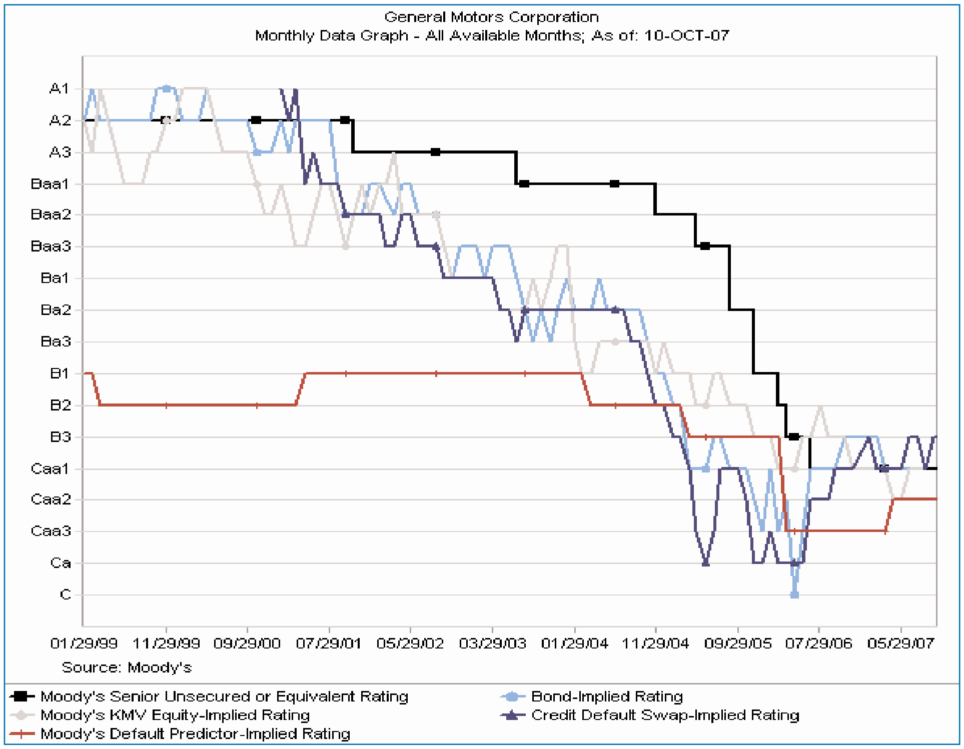
- Describing the Market Implied Ratings platform, datasets, and applications;
- Providing answers to frequently-asked questions that have come up in conversations with clients; and
- Furnishing guidance on how clients can use the data. This draws upon existing and ongoing research by the Credit Strategy Group and other Moody's research areas.

[1] *Munves, Jiang and Lam (August 2006)*

# II: Overview and Background

Market Implied Ratings is a straightforward product. For over 3,000 entities it collects signals from five different sources (Moody's ratings, the bond, credit default swap, and equity markets, and an accounting ratio-based model) and displays them on the Moody's rating scale. Figure 2 shows an example of Market Implied Ratings data for General Motors. It demonstrates how gaps between Moody's ratings and the various implied ratings open up, and then close over time. In the case of GM, the markets' views were more pessimistic than Moody's for several years before the differential narrowed, mostly by Moody's rating catching up with the lower market trading levels.

**Figure 2: General Motors' Moody's Rating and Implied Ratings (1999 - 2007)**




**FAQ 3: How do clients get access to MIR?**

There are several ways that clients can access Market Implied Ratings data. They can visit moodys.com (the source of Figure 2); receive direct data feeds; or install an Excel add-in to link their spreadsheets to Moody's database.

## The comparative analysis at the heart of MIR

FAQ 4: What is a ratings gap?

A key aspect of the platform is that the four non-Moody's metrics are displayed relative to the issuer's senior unsecured Moody's rating or its equivalent. This gives rise to concept of positive or negative ratings gaps. For example, let's take an issuer with a Moody's rating of Baa2. We assume further that its CDS spread is in line with the median 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 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 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 trade in line with the levels suggested by its Moody's rating, then the ratings gap is zero.

A key aspect of the platform is that the four non-Moody's metrics are displayed relative to the issuer's senior unsecured Moody's rating

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.* As we discuss later, our research shows differences in the behavior of a company's obligations in different markets, for example, bonds vs. CDS. Investors can compare the varying signals, and focus on those which best fit their needs.
- *It isolates issuer-specific changes.* As we describe in the sidebar titled Ford's Trading History (p.6), 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 price and spread reference point in the corporate bond and CDS markets.* Whether an issuer trades "rich" or "cheap" for its rating is a common reference point in the corporate debt markets. The use of this familiar framework by the Market Implied Rating platform makes its output intuitive for credit professionals. As we show in Section IV, the use of debt ratings as reference points also means that implied ratings tend to track back towards the level suggested by the issuers' ratings. This adds value to the MIR data's predictive power.

FAQ 5: Does MIR isolate issuer-specific changes in value?

**Figure 3: Map Between Moody's Ratings and Implied Rating Values**

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

II: Overview and Background *(continued)*

## Providing a global comparison

**FAQ 6: Is MIR a global product?**

Market Implied Ratings is a global product. It encompasses entities from 122 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; it needs to have a Moody's rating, and it must have publicly traded bonds, shares, or CDS with reliable prices.[2]

**An entity's inclusion in the platform is essentially determined by two factors**

### Figure 4: Market Implied Ratings Coverage

| | Bond-Implied | Equity-Implied | CDS-Implied | MDP-Implied |
|---|---|---|---|---|
| **Number of Issuers** | **2,900** | **1,800** | **2,000** | **1,600** |
| Investment Grade | 66% | 79% | 75% | 51% |
| Speculative Grade | 34% | 21% | 25% | 49% |
| **Geographic Breakdown** | | | | |
| Americas | 68% | 66% | 55% | 72% |
| Asia | 5% | 5% | 9% | 4% |
| EMEA | 22% | 18% | 27% | 15% |
| Japan | 5% | 10% | 9% | 9% |
| Data from | 1/1/1999 | 1/1/1999 | 1/1/2001 | 1/1/1999 |

**FAQ 7: Why don't we have regional versions of MIR?**

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 comes up most often for the bond-implied ratings dataset. There are two reasons for calculating implied ratings only on a global scale.

*2 To be included in the Moody's Default Predictor (MDP) implied ratings dataset, an issuer must have a Moody's rating and regularly published financial statements. Also, only industrial and utility entities get MDP-implied ratings.*

## Ford's Trading History: Market Implied Ratings and Relative Performance

The Market Implied Rating platform calculates median credits for the CDS and bond datasets on a daily basis. For example, all eligible Baa2-rated bonds are used to calculate the Baa2 bond spread curve, all Baa3-rated issues are used to calculate Baa3 curve, and so on. For an issuer's implied rating to change, its spread must outperform or underperform the movements of its peer group with the same implied rating.

Figure A: Relationship Between Ford Bond Spread and Its Bond-Implied Rating

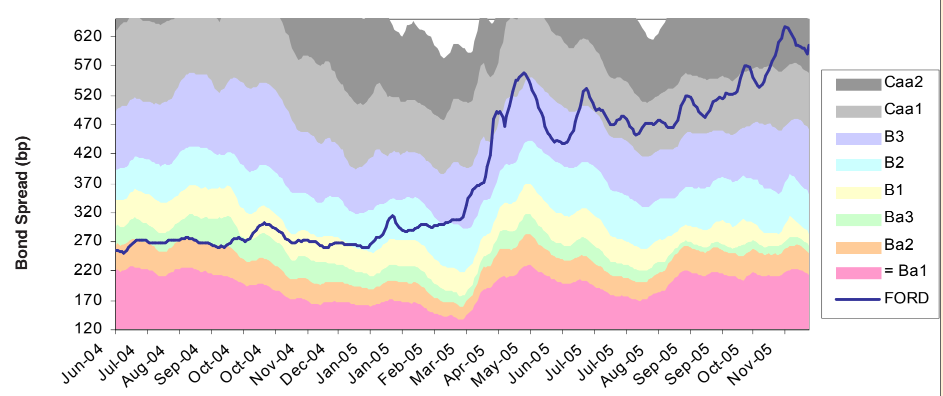
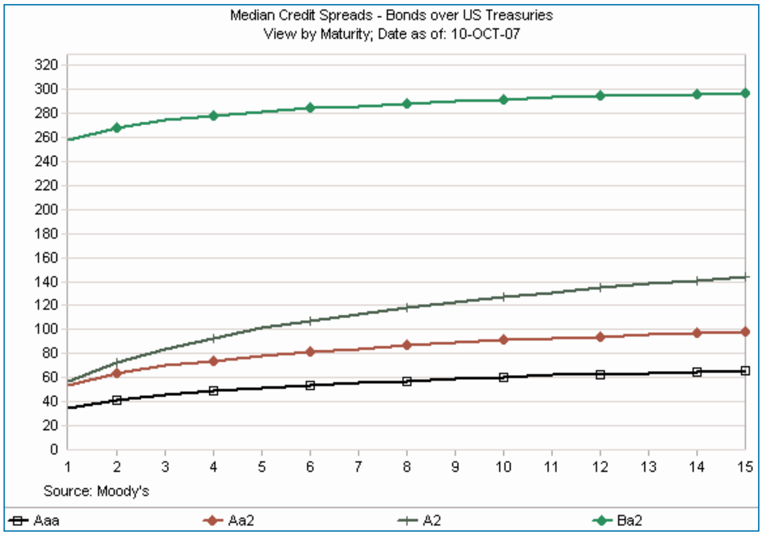


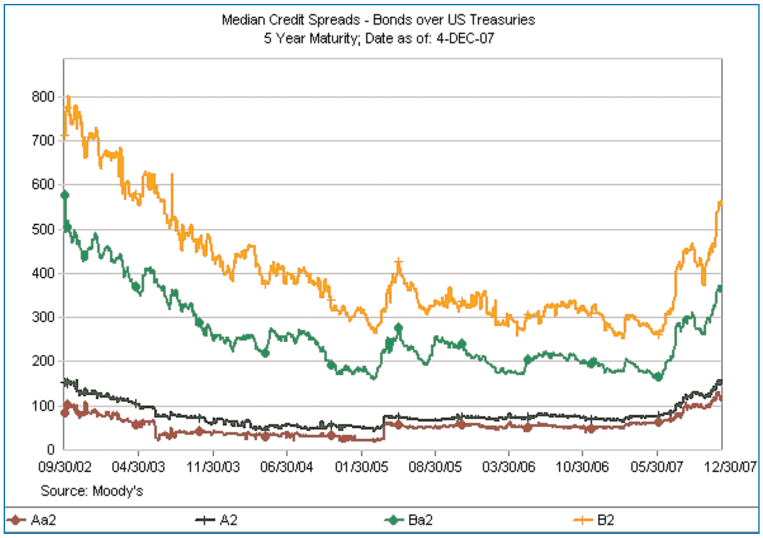

Figure A clearly illustrates this dynamic using a Ford bond as an example. The colored areas outline the value range of the spreads to which implied ratings are assigned. From August 2004 to March 2005, the bond-implied rating for the Ford issue fell three notches from Ba2 to B2. This represents an underperformance compared to the broad market. In other words, Ford's bond spread had widened relative to the broad market during the period.

## II: Overview and Background *(continued)*

### Figure 5a: Selected Median Credit Spread Curves




### Figure 5b: Selected Median Credit Spreads Over Time




**FAQ 8: How does MIR handle non-US dollar bonds?**

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. Please see Appendix I for details. Thus, all credit spreads are on a dollar basis (option-adjusted spread over the Treasury curve, to be precise). All issues are therefore treated the same, obviating the need to compare issues in one currency to credit curves in that currency. Users wishing to see relative rankings of implied ratings from issuers in one country can easily obtain the data via the Ratings Interactive tool on moodys.com.

The second reason is that we need a lot of data to produce robust common benchmarks for each of the four datasets. Specifically, we calculate benchmark implied ratings for each of the 21 Moody's rating categories shown in Figure 3. And for the bond dataset, for each rating category we must calculate full credit term structures of 1 to 12 years in duration. If we split the data sets into different 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.

We offer median credit spreads for the bond and CDS markets on the MIR site on moodys.com, with data starting on January 1, 1999 for the bond dataset and on January 1, 2001 for CDS. Figures 5a and 5b provide examples of bond credit spread curves and spread movements over time. These also represent the global dataset on a dollar basis.[3]

[3] *Currency considerations are more relevant for bonds than for CDS, of course.*

## What you see is generally what you get

FAQ 9:
How much data scrubbing do we do?

The explicit assumption underlying Market Implied Ratings is that the market prices of securities have high information content

The explicit assumption underlying Market Implied Ratings is that the market prices of securities have high information content. Thus, beyond quality assurance routines and the limited exceptions described below, there is no data scrubbing.[4] For example, we do not remove bonds or CDS that we deem to be "outliers", or smooth time series that appear to be "too noisy". These are hard judgments to make systematically, and different users have different ideas of what constitutes an "outlier" or "noise". Standards can change, too, depending on levels of market volatility and credit risk.

Moreover, we do not manipulate the data to achieve an idealized result. This is despite the very well-ordered structure of many of our research results - for example, see Figure 18 on p.24.

We have found that the product's straightforwardness, particularly for bond- and 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. The methodologies for equity- and MDP-implied ratings are, by necessity, more complicated. For equity-implied ratings we are extracting a credit risk signal from equity market data, combined with information on entities' liabilities and the volatility of their assets. And for MDP-implied ratings we derive default risk signals from a range of company financial ratios.

[4] *While we avoid filtering market data, the inputs to our models are carefully checked.*

# III: The Implied Ratings Datasets and Models

**The valuation of an issuer's debt, equity, or default risk in relation to its Moody's rating lies at the heart of Market Implied Ratings**

In this section we first describe how we determine the issuer-level Moody's rating used in Market Implied Ratings. We then cover the four datasets contained in the Market Implied Ratings product; bond-implied ratings, CDS-implied ratings, equity-implied ratings, and Moody's Default Predictor (MDP)-implied ratings.

## Determining the Moody's rating for an issuer

The valuation of an issuer's debt, equity, or default risk in relation to its Moody's rating lies at the heart of Market Implied Ratings. Many issuers have a variety of Moody's ratings associated with them, reflecting the complexities of their corporate structures and balance sheets, as well as bond issue-specific factors. Yet there is an obvious need to utilize comparable ratings among issuers, and we do this by using each entity's "senior unsecured or equivalent" rating. We explain the process of determining the senior unsecured or equivalent rating in Appendix II.

**FAQ 10: What are our bond inclusion criteria?**

### 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 (including euro legacy currencies), sterling, yen, Swiss francs, Canadian dollars, or Australian dollars
- Have a modified 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

**III: The Implied Ratings Datasets and Models** *(continued)*

This use of ratings as value reference points helps make the MIR data especially useful

## Bond-Implied Ratings

### The central role of ratings

While issuers in the bond and CDS markets tend to trade in relation to their ratings, we do not, of course, suggest that market participants think the ratings are always correct. Indeed, Figure 1 suggests that the market's view of an issuer's creditworthiness usually varies from Moody's.  But this use of ratings as value reference points helps make the MIR data especially useful.

### Why bonds?

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 a full cycle of credit busts and booms, significantly strengthens our research results.  By contrast, the CDS data is only available from 2001, and in the early years contained almost only investment grade issuers.

A second point is that the inclusion of the bond dataset allows MIR subscribers to use the data to analyze arbitrage opportunities between an issuer's bonds and CDS.

Finally, the bond dataset includes issue and issuer-level implied ratings and other information, all of which is available to subscribers.  Figure 6 shows a screen grab of issue-level information for a sample entity.  Such data allows subscribers to use MIR to analyze issuer-specific curve trades.

**Figure 6:  Sample Issue-level Data**

**MARKET IMPLIED RATINGS**

*Moody's Single Issuer Report*

General Motors Corporation
Date as of: 22-OCT-07

**Time Period** All Available Days   Printer Friendly Version   Download to Excel   Graph   Help

| Date | Moody's Senior Unsecured or Equivalent Rating | Outlook | Bond-Implied Rating | Equity-Implied Rating (Moody's K·M·V) | Credit Default Swap-Implied Rating | Moody's Default Predictor-Implied Rating | Bond-Implied Gap | Equity-Implied Gap | Credit Default Swap-Implied Gap | Moody's Default Predictor-Implied Gap |
|---|---|---|---|---|---|---|---|---|---|---|
| 10/22/2007 | Caa1 | POS | B3 | B3 | Caa1 | Caa2 | 1 | 1 | 0 | -1 |
| 10/19/2007 | Caa1 | POS | B3 | B3 | Caa1 | Caa2 | 1 | 1 | 0 | -1 |
| 10/18/2007 | Caa1 | POS | B3 | B2 | Caa1 | Caa2 | 1 | 2 | 0 | -1 |
| 10/17/2007 | Caa1 | POS | B3 | B3 | B3 | Caa2 | 1 | 1 | 1 | -1 |
| 10/16/2007 | Caa1 | POS | B3 | B2 | B3 | Caa2 | 1 | 2 | 1 | -1 |
| 10/15/2007 | Caa1 | NEG | B3 | B2 | B3 | Caa2 | 1 | 2 | 1 | -1 |
| 10/12/2007 | Caa1 | NEG | B3 | B2 | B3 | Caa2 | 1 | 2 | 1 | -1 |
| 10/11/2007 | Caa1 | NEG | B3 | B3 | B3 | Caa2 | 1 | 1 | 1 | -1 |
| 10/10/2007 | Caa1 | NEG | B3 | B3 | B3 | Caa2 | 1 | 1 | 1 | -1 |
| 10/9/2007 | Caa1 | NEG | Caa1 | B3 | B3 | Caa2 | 0 | 1 | 1 | -1 |
| 10/8/2007 | Caa1 | NEG | Caa1 | B3 | B3 | Caa2 | 0 | 1 | 1 | -1 |
| 10/5/2007 | Caa1 | NEG | Caa1 | B3 | B3 | Caa2 | 0 | 1 | 1 | -1 |
| 10/4/2007 | Caa1 | NEG | Caa1 | B3 | B3 | Caa2 | 0 | 1 | 1 | -1 |
| 10/3/2007 | Caa1 | NEG | Caa1 | B3 | B3 | Caa2 | 0 | 1 | 1 | -1 |
| 10/2/2007 | Caa1 | NEG | B3 | B3 | B3 | Caa2 | 1 | 1 | 1 | -1 |

III: The Implied Ratings Datasets and Models *(continued)*

## Building the bond-implied ratings dataset and calculating bond spreads

We start with daily feeds from our vendors of bond prices, spreads, and indicative information such as issuer name, issue identifier, 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 p.9) 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 30,000 issues. Ultimately, around 12,500 issues pass through the inclusion criteria to make up the bond-implied ratings dataset.

**FAQ 11:
What are the bond price information sources?**

We calculate our daily prices and option-adjusted spreads from a blend of Reuters, Markit, and TRACE data, and use other sources to provide additional quality checks. The general rule is that the more recent the traded price and the larger the transaction, the more we rely on it. 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.

Determining the credit spread for bonds with options (only around 5% of the dataset) is a more complex exercise. We discuss these and other credit curve-building issues in Appendix III.

## Calculating median credit spreads for bond-implied ratings

Once we have fixed the list of eligible bonds and their spreads, the next step is to calculate the median credit spreads.[5] The group of bonds used to calculate the median credit spreads is a subset of the bond-implied ratings dataset. Specifically, it does not include two types of issues, which make up a maximum of 10% of the total:

- Bonds sold by issuers on Moody's Watchlist for upgrade or downgrade. Such issues could well see their Moody's ratings change in the near future, and thus usually trade in line with entities rated lower or higher than their current ratings.
- Bonds denominated in yen and Australian dollars. Peculiarities of these markets mean that for a given rating category the issues trade quite tight for their ratings on a spread basis, even when accounting for currency effects. Thus, their inclusion would compromise the global standard attributes of the median credit spreads.

We are now ready to build the credit curves. For each rating category we group the bonds into duration buckets of up to 12 years, pick the median spread point, and use a non-linear regression to fit a curve through the medians.

*5 Credit market spreads are usually calculated as market-weighted means. This approach has the advantage of providing a measure of the spread "available" to investors in the asset class. But it suffers from two disadvantages. Firstly, spreads for a given rating category can be highly influenced by the behavior of a limited number of large issues. And secondly, the distribution of credit spreads for a given rating category is typically skewed to the downside. That is, there is a long and fat tail of wider spreads, and the distribution of this tail often has a disproportionate impact on the mean spread level. We therefore believe that the median spread represents a truer assessment of the spread level implied by the market for a given rating category.*

**III: The Implied Ratings Datasets and Models** *(continued)*

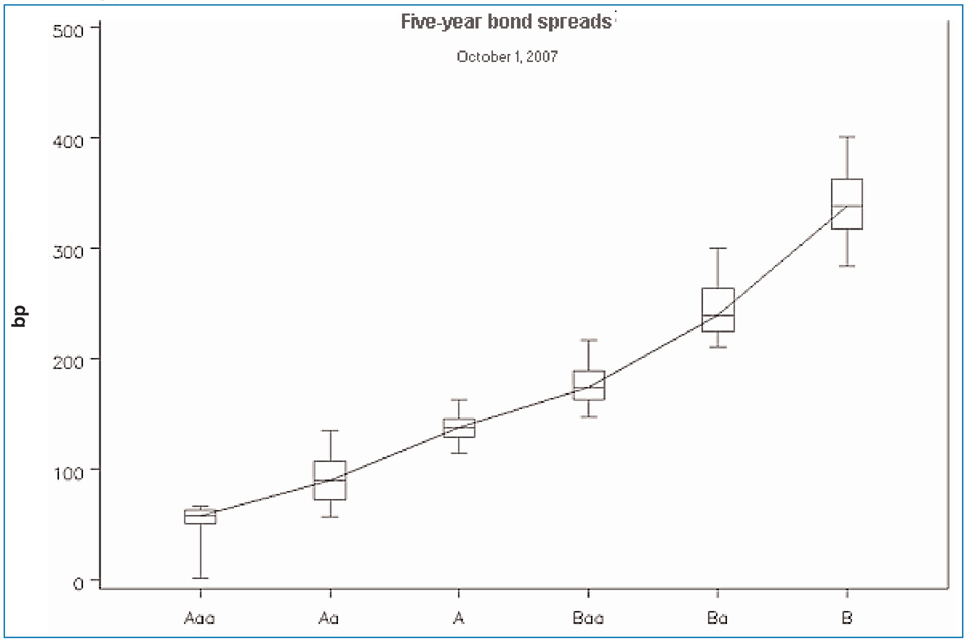
**FAQ 12: How often is MIR updated?**

Each curve represents the typical spread for a bond with a given duration or maturity in a given rating category. As we showed in Figure 5a, the curves are usually upward sloping and approximately parallel, as would be expected. Both the credit curves and the implied ratings are updated daily. We make them available to MIR subscribers on moodys.com in the interests of transparency (so investors can see the median levels used to determine the implied ratings) and to enhance the value of the product to clients. The curves are published on both a maturity and a duration basis.

**For a given duration point, the lower the debt rating the higher the median credit spread**

For a given duration point, the lower the debt rating the higher the median credit spread. But there is considerable overlap in the ranges of spreads per rating. Indeed, this is reflected in the ratings gap distributions, as shown on the cover. Figure 7 demonstrates this for five-year maturity debt. The middle point, box, and line represent the median observation, the inter-quartile range, and the range between the minimum and maximum observations, respectively. Further, there is little overlap between the middle 50% of observed spreads for each rating category.

**Figure 7: Disribution of Spreads for Bonds by Rating Category (5-year maturity)**




**FAQ 13: How do we set the borders between MIRs?**

A final note concerns the boundaries between each implied rating category. As can be seen from the Ford sidebar on p.6, bonds or CDS that fall in a certain range around a median credit spread receive the implied rating associated with that spread. We determine the boundary between the bands by taking the geometric mean of the two neighboring spreads.[6]

[6] *The geometric mean is the square root of the product of the two spreads.*

## III: The Implied Ratings Datasets and Models *(continued)*

### Calculating issue-level bond-implied ratings

**FAQ 14: How do we adjust for bond maturities?**

Once we have established the credit curves we can calculate the issue-level bond-implied ratings. We do this for all eligible issues in all currencies, including those on the Watchlist. Each median spread curve is assigned a numerical value that corresponds to its Moody's rating, per the mapping scheme in Figure 2. Then for a given issue, we look at its spread and duration, and place it in the correct position in respect to the curves. This means that the implied rating for each issue is adjusted for its duration (or maturity). Most issues do not sit exactly on a curve. Rather, they end up somewhere between the curves, and thus receive corresponding fractional values.

### Calculating issuer-level bond-implied ratings

**FAQ 15: How do we calculate bond issuer-level implied ratings?**

We determine the issuer-level bond-implied ratings by averaging each entity's issue-level implied rating. Larger issues are given greater weight in the calculation, reflecting their better pricing characteristics. We underweight long- and short-duration issues due to the lower information content of the prices of such issues.

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[7]. This last step provides the bond-implied ratings gap.

An example might help explain the process. Let's take an issuer that with a senior unsecured or equivalent rating of Baa1. It has two bonds outstanding, one senior and one subordinated. The senior bond has a rating of Baa1 and a bond-implied ratings gap of 0, while the subordinated issue is rated Baa2 and has 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 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.

**How volatile are implied ratings, especially compared to Moody's ratings?**

### High volatility of implied ratings compared to Moody's ratings

Before leaving the subject of bond-implied ratings, we would like to address a topic on which we often receive questions from users; how volatile are implied ratings, especially compared to Moody's ratings?

**FAQ 16: How volatile are market-implied ratings?**

As might be expected (and as we note in the Introduction), implied ratings are a lot more volatile than Moody's ratings. Amongst 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.[8] Figure 8 shows the percentage of Moody's issuer ratings and bond-implied ratings which change each year.

---

[7] *Please see Appendix II for a description of how we determine an issuer's senior unsecured or equivalent rating.*

[8] *See Section III and Munves, Jiang and Lam (August 2006)*

### III: The Implied Ratings Datasets and Models *(continued)*

**Figure 8: Average Annual Ratings Change Rates – 1999 to 2007**

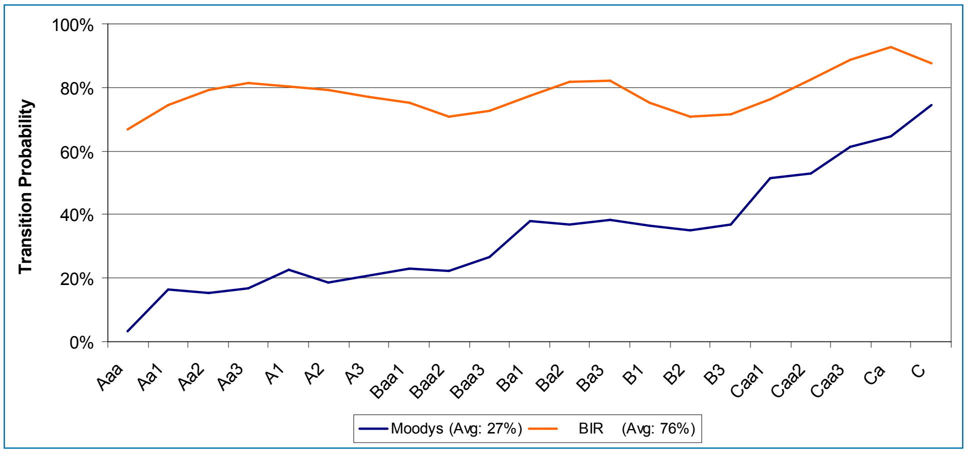
| | Moody's | Bond-Implied Ratings |
|---|---|---|
| Rating Action Rate | 24% | 98% |
| Large Rating Action Rate* | 4% | 28% |

*Changes of two notches or more
Source: Credit Policy Group, Corp. Bond Rating Performance Report

The ratings change rate for bond-implied ratings is almost 100%, while the Moody's rate is only 28%. Furthermore, large ratings changes are much more frequent for implied ratings than for Moody's ratings. Note also that Figure 8 only measures the percentage of ratings that have changed at least once in a year. When Moody's ratings change, it's relatively rare that they change more than once a year. By contrast, as the General Motors example in Figure 2 indicates, implied ratings usually change multiple times over a 12-month period.

Figure 9 provides an interesting contrast in the volatility patterns between Moody's ratings and bond-implied ratings.

**Figure 9: Rate of 1-Year Change for Moody's Ratings and Bond-Implied Ratings per Ratings Category**

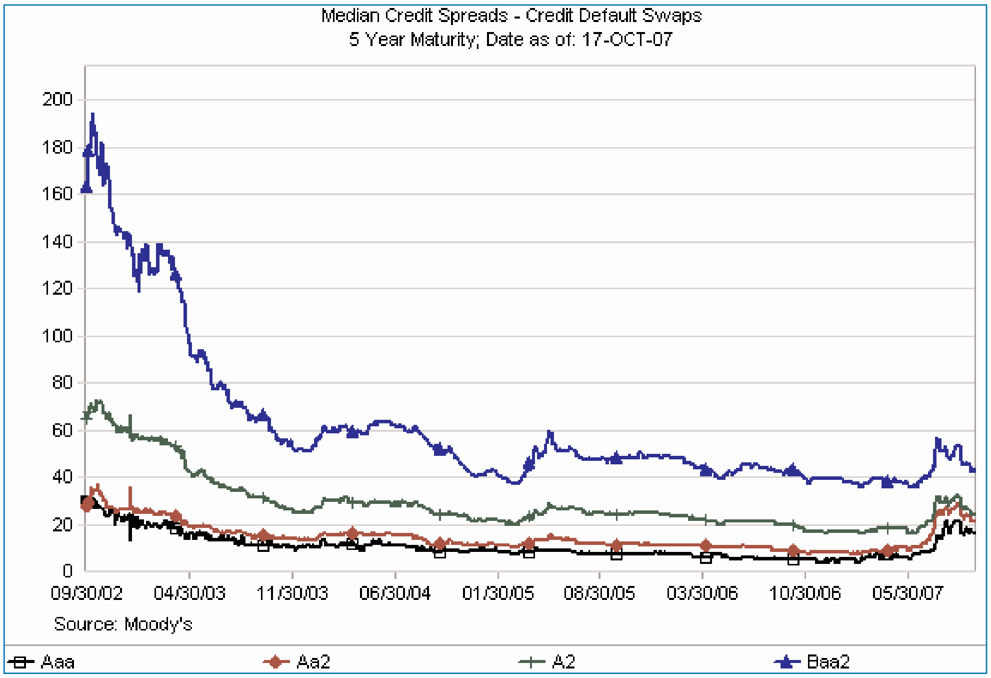



The lower the Moody's rating, the more likely it is to change. On the other hand, the rate of change for implied ratings rises only modestly between the upper end of investment grade and the lower end of high yield.[9] We can conclude from Figure 9 that while it takes a smaller spread movement to cause a change in an investment grade implied rating, this consideration is offset by a lower level of bp spread volatility.

*[9] The ratings change rate in Figure 9 is calculated on an annual cohort basis. That is, a rating is counted as "changed" if it is different at the end of the year 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.*

## III: The Implied Ratings Datasets and Models *(continued)*

**Figure 10: Selected CDS Spreads over Time**




## CDS-Implied Ratings

Credit default swaps are a relatively recent financial innovation, but they have transformed the credit markets. Their original use was to provide a form of insurance against default. They now often serve as bond substitutes, and bring several advantages to this role.

**FAQ 17: Why do we use only 5-year CDS?**

CDS also have many advantages over bonds from a modeling point of view. Instead of multiple bonds with different characteristics, there is usually just one contract for each reference entity,[10] and 85% or more of trading takes place in 5-year maturity contracts. This means that we can rely on the 5-year point in the curve to determine the CDS-implied ratings, and have no need to build credit term structures for each rating category, as we do for the bond dataset.

**FAQ 18: What is the source of our CDS pricing?**

Our CDS price source is Markit Group. While CDS denominated in different currencies trade in line with each other, our policy is to use spreads of US dollar-denominated contracts, unless these are not available. In that case, we take spreads on contracts denominated in other currencies.[11]

As with the bond-implied ratings, our CDS median credit spreads are updated daily. The data is available beginning January 1, 2001. The median credit spreads are calculated directly from market observations. The only deviation from this is when the spread curve inverts, e.g., when the median Aa3 spread is wider than the median A1 spread. In such cases (which are rare) we use a scheme that interpolates the affected median credit spreads between the two spread points on either side of the inverted part of the credit curve.

Figure 10 shows representative CDS spreads over time, as available on moodys.com.

*[10] We say "usually" because some entities, especially banks, will have senior and subordinated CDS contracts, i.e., contracts with reference securities with different degrees of subordination. However, their seniority is easily identified.*

*[11] Specifically, for the major currencies, the priority order after US dollar-denominated CDS is euros, sterling, Canadian dollars, Swiss francs, yen, and Australian dollars.*

## Equity-Implied Ratings

For bond- and CDS-implied ratings the levels 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 a great deal of insight regarding the default risk of the firm, when combined with the liabilities structure and a measure of asset volatility. But market capitalization is not a direct measure of default risk. Thus, another approach must be taken to extract credit risk signals from equity market data.

One response to this problem is based on an extension of the so-called Merton contingent claims approach to modeling default risk from share prices. This has been substantially refined by Moody's KMV to produce their widely used expected default frequency (EDF) metrics over a twenty-year period[12]. At Moody's KMV, we find that the equity based signal of default probability, as indicated by the Moody's KMV public EDF credit measure, provides a strong and timely signal regarding the likelihood of a firm defaulting across the entire population of firms with publicly traded equity.

FAQ 19:
How do we map from EDF values to equity-implied ratings?

### How are EDF values mapped to implied ratings?

The mapping from EDF measures to implied ratings is determined by median EDF measures of firms in ratings classes using Moody's KMV's "spot median" methodology. The spot median for a major rating class captures the median of the most recent month's EDF values for all North American non-financial firms that fall into this rating class.

The value of the firm's equity as measured by market capitalization provides a great deal of insight regarding the default risk of the firm

**Figure 11: Selected CDS Spreads over Time**

| Major Rating | Median EDF (Notation) | Median EDF Computation |
|---|---|---|
| Aaa | $M_{Aaa}$ | Median across firms with rating Aaa |
| Aa | $M_{Aa}$ | Median across firms with rating Aa1, Aa2 or Aa3 |
| A | $M_{A}$ | Median across firms with rating A1, A2 or A3 |
| Baa | $M_{Baa}$ | Median across firms with rating Baa1, Baa2 or Baa3 |
| Ba | $M_{Ba}$ | Median across firms with rating Ba1, Ba2 or Ba3 |
| B | $M_{B}$ | Median across firms with rating B1, B2 or B3 |
| Caa | $M_{Caa}$ | 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 | $M_{Ca}$ | Geometric mean of MCaa and 35% |
| C | $M_{C}$ | 35% |

Specifically, the data used to get the spot median EDF for a major rating class is summarized in Figure 11. There is generally some dispersion in EDF measures by grade, just as there are dispersions of bond and CDS spreads by grade that reflects market perception of risk differences within grades. If there are very few firms in a rating category, the median EDF will move around more due to single-firm risk changes.

*12 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 recent enhancements to the model. Korablev and Dwyer (2007) provides recent validation results.*

## III: The Implied Ratings Datasets and Models *(continued)*

Due to small samples, the median EDF level of a rating is not always better than the median EDF of the rating that is one notch below it. For example, the median EDF level of an A2 credit may not always be better (ie, lower) than the median EDF of an A3 credit. This is particularly true for high-quality firms that have the most agency rating bands; differences between fine grades are measured within a few basis points of each other. Due to these issues, Moody's KMV uses the broader data on major letter rating categories to set the bands and then maps fine grades between these by a geometric means approach, as explained below. This exercise is repeated at the end of each month. It should be noted that Moody's KMV sets the mapping to very low-quality grades as constant. Specifically, we map Ca credits to the geometric mean of the Caa EDF and an EDF of 35%, and we map C to 35%. Setting constants to low-grade categories is due to the limited number of firms in such categories, and calibrating the medians month by month will yield volatile mappings. The constants used are calibrated from a long-term pooled sample.

**Figure 12: Interpolated median EDF numbers by finer rating buckets**

| Rating | Median EDF | Median EDF Interpolation Scheme |
|---|---|---|
| Aaa | $M_{Aaa}$ | $M_{Aaa}$ |
| Aa1 | $M_{Aa1}$ | $(M_{Aa2})^{1/3} (M_{A2})^{2/3}$ |
| Aa2 | $M_{Aa2}$ | $M_{Aa2}$ |
| Aa3 | $M_{Aa3}$ | $(M_{Aa2})^{2/3} (M_{A2})^{1/3}$ |
| A1 | $M_{A1}$ | $(M_{Aa2})^{1/3} (M_{A2})^{2/3}$ |
| A2 | $M_{A2}$ | $M_{A2}$ |
| A3/A- | $M_{A3}$ | $(M_{A2})^{2/3} (M_{Baa2})^{1/3}$ |
| Baa1 | $M_{Baa1}$ | $(M_{A2})^{1/3} (M_{Baa2})^{2/3}$ |
| Baa2 | $M_{Baa2}$ | $M_{Baa2}$ |
| Baa3 | $M_{Baa3}$ | $(M_{Baa2})^{2/3} (M_{Ba2})^{1/3}$ |
| Ba1 | $M_{Ba1}$ | $(M_{Baa2})^{1/3} (M_{Ba2})^{2/3}$ |
| Ba2 | $M_{Ba2}$ | $M_{Ba2}$ |
| Ba3 | $M_{Ba1}$ | $(M_{Ba2})^{2/3} (M_{B2})^{1/3}$ |
| B1 | $M_{B1}$ | $(M_{Ba2})^{1/3} (M_{B2})^{2/3}$ |
| B2 | $M_{B2}$ | $M_{B2}$ |
| B3 | $M_{B3}$ | $(M_{B2})^{2/3} (M_{Caa2})^{1/3}$ |
| Caa | $M_{caa}$ | $M_{caa}$ |
| Ca | $M_{ca}$ | $M_{ca}$ |
| C | $M_{c}$ | $M_{c}$ |

Before deriving fine grades mapping, the category medians are checked and adjusted when necessary to ensure a monotonic relationship to rating grades, i.e., a riskier rating grade should always correspond to a higher EDF value. For example, the mapping to Aa2 is required to be at least one basis point below that of A2. This adjustment is rarely triggered.

The fine rating classes are based on the weighted geometric mean of the neighboring major rating categories. The median EDF should increase at an increasing rate as the ratings deteriorate, i.e., the median EDF should be a convex function of the ratings. For example, if a median EDF for Baa2 is 20 bp and a median EDF 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, we use a geometric interpolation scheme across the major rating buckets to get the finer rating medians. The geometric mean of two numbers is closer to the smaller number, thereby ensuring convexity. Once the medians corresponding to major ratings are decided, the finer rating can be expressed as the weighted geometric mean of the median EDF values corresponding to the neighboring major rating categories. This is described in Figure 12.

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 of 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:

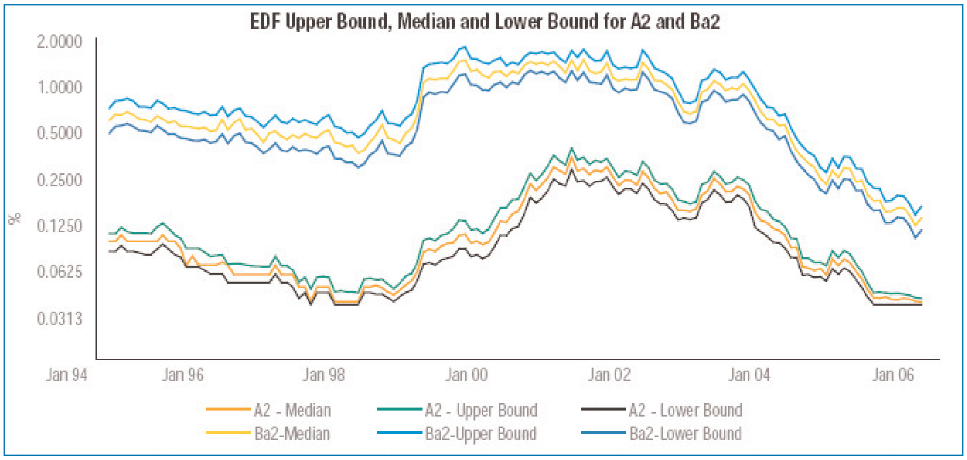
$$Lower\ bound\ of\ \ Aa\sqrt{0.02 \text{ x } .03} = 0.024$$

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

## III: The Implied Ratings Datasets and Models *(continued)*

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 13: Variation of median EDF and bounds for ratings A2 and Ba2**




Once we have the EDF ranges for each category, we are able to assign an equity-implied rating for a given EDF value. As shown in Figure 13, the median EDF value for each credit category varies a lot over time. For example, the median EDF for A2 varied from 25 bp in 2000 to 3 bp in 2007. Secondly, the range of EDFs covered in even the finer rating buckets can be fairly wide. For example, at the beginning of 2004, all firms with EDF values between 8 bp and 12 bp had the same credit category, A2. Similarly, all firms with EDF values between 60 bp and 100 bp fall in the Ba2 category.

III: The Implied Ratings Datasets and Models *(continued)*

## Comparing EIR Measures between EDF 8.0 and 7.1 Models

In June 2007, Moody's KMV released the EDF 8.0 model.[13] The EIR measures from the EDF 8.0 and EDF 7.1 models differ in the following ways:

- The EDF 7.1 model has an EDF ranges from 2 bps to 20%, while the EDF 8.0 model expanded the range from 1 bps to 35%. This allows the new EIR measure to better distinguish high quality companies, especially in a benign environment of a credit cycle, when fewer companies have EDF values that reach the floor.
- The EDF 7.1 model's lookup table for worst categories (Caa2 and worse) is static and does not vary with credit cycle. In the EDF 8.0 model, this has become dynamic.
- In the EDF 7.1 model, the EIR measure is based on EDF credit measures that is rounded to basis points, while in the EDF 8.0 model, we derive the EIR before any rounding in the EDF credit measure.
- In the middle of the credit spectrum, the EIR measures under EDF 7.1 and 8.0 models should be largely the same.

Figure 1 compares the distributions of Moody's Estimated Senior Rating and of EIRs from these two EDF models in the end of 2006. It is noted that the EIR under the EDF 7.1 model has a high concentration on Aaa, and has no observations in Aa1, Aa3, A1, A3, Baa1, Caa3 and C. Under the EDF 8.0 model, however, the EIR fills all spectrums of the credit categories. Consequently, the EDF 8.0 model makes the equity-implied ratings more useful in distinguishing credit quality at the high end of the spectrum during the current stage of the credit cycle.

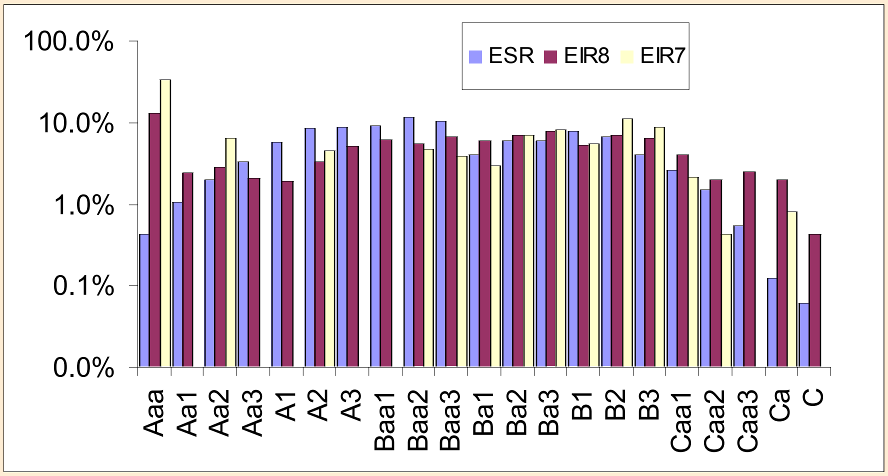



FIGURE 1. Distribution of Estimated Senior Rating, EIR under the EDF 8.0 and 7.1 models on December 31, 2006

13 *For an overview of the new model, see Dwyer and Qu (2007).*

**Feature** *(continued)*

## Default Predictor-implied ratings are derived from a statistical credit scoring model

FAQ 20: Which financial ratios underlie the MDP model?

## The six accounting ratios were selected from a list of 43 ratios commonly associated with fundamental analysis

FAQ 21: MDP-IRs and the underlying ratios.

## The final MDP-implied rating is not a weighted average of the univariate-implied ratings

# Default Predictor-Implied Ratings

Default Predictor-implied ratings[14] are derived from a statistical credit scoring model developed by Moody's. The model is designed to rank-order corporate, non-financial obligors by default risk over a one-year horizon. The model uses six accounting-based financial ratios, lagged three months from the time of the report date (quarterly statements are used if available, otherwise annual statements are used), to compute a model "score." The score is similar to a probability of default (PD) in the sense that a higher score indicates a higher (one-year) default probability. The scores are then mapped to Moody's long-term debt rating scale with the interpretation that higher-rated issuers have lower one-year PDs. Moody's Default Predictor (MDP) does not rely on market-based data, and as a result, generally gives more stable estimates of credit risk than do those based on market indicators such as stock prices, bond prices or CDS premia.

The six accounting ratios were selected from a list of 43 ratios commonly associated with fundamental analysis, including measures of coverage, leverage, liquidity, size, growth, and volatility. Each ratio was constructed in accordance with the methodologies used by Moody's analysts and detailed in published materials. After a thorough selection process, the following combination of ratios was found to have the greatest predictive power on an in-sample basis. The ratios were also validated through the use of a hold-out sample:

- (EBIT + 1/3 Rent Expense) / (Interest Expense + 1/3 Rent Expense + Preferred Dividends / 0.65)
- Adjusted Debt / Adjusted Capital
- Cash and Equivalents / Total Assets
- 5-yr Average of Sales / 5-yr Standard Deviation of Sales
- Retained Cash Flow / Adjusted Debt
- One-year Growth Rate of Total Assets

The six accounting ratios are each mapped into "one-year default rate equivalents" using non-parametric transformations. This intermediate mapping is done to account for the non-linear relationships between the various ratios and default probability. The transformed ratios are then used as inputs into a probit model that computes the model score, which is then mapped to a rating. We also produce univariate-implied ratings for each of the six inputs using the transformed ratios; i.e. an issuer with an MDP-implied rating of A1 might have: Aa2 coverage, Baa1 leverage, etc. It should be noted that the final MDP-implied rating is not a weighted average of the univariate-implied ratings. To the contrary, it may be the case that an obligor has a higher MDP-implied rating than any of the six univariate-implied ratings.

Recently, the method by which model scores and the six accounting ratios are mapped to ratings was revised. To account for changes over time in the distributions of the six accounting ratios that drive MDP-based ratings, the previous static mappings were replaced by mappings that are updated monthly. The mappings are calculated such that the overall distributions of MDP- and univariate-implied ratings match the distribution of Moody's senior unsecured (or equivalent) ratings as of the date the mappings are constructed. For example, if, at the time a new monthly mapping is calculated, 5% of corporate non-financial issuers hold Aaa ratings, then the Aaa/Aa1 MDP-implied rating cutoff is calculated so that 5% of MDP-implied ratings are Aaa. If 6% of the corporate non-financial universe holds Aa1 ratings, then the Aa1/Aa2 cutoff is calculated such that 6% of MDP-implied ratings are Aa1, and so forth. The same algorithm is applied to each of the six accounting ratios in turn.

14 *See Fons and Viswanathan (December 2004) and Fons and Woolley (June 2007).*

# IV. Applied Research

## The bedrock of the analysis consists of ratings gap-conditioned transition matrices

In this section we turn our attention to the practical applications of Market Implied Ratings. To a large degree this is a review of published research from the Credit Strategy Group, which addresses questions from clients and Moody's analysts about the significance and interpretations of ratings gaps and implied ratings levels for the various datasets.

### Underneath it all; ratings gap-conditioned transition matrices

The bedrock of the analysis consists of ratings gap-conditioned transition matrices. Figure 14 provides a sample transition matrix, for entities with ratings gaps of zero in the bond dataset.

**Figure 14: Transition Rates for issuers with Bond-Implied Ratings Gaps of zero**

| From | | To [12 Month] | | | | | | | | | | | | | | | | | | | | | Up | Down | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cnt | Rtg | Aaa | Aa1 | Aa2 | Aa3 | A1 | A2 | A3 | Baa1 | Baa2 | Baa3 | Ba1 | Ba2 | Ba3 | B1 | B2 | B3 | Caa1 | Caa2 | Caa3 | Ca | C | Grade | Grade | Default | WR |
| 2252 | Aaa | 97.9% | 0.6% | 0.7% | 0.1% | 0.5% | | | | | | 0.0% | | | | | | | | | | | 0.0% | 2.0% | 0.00% | 0.2% |
| 709 | Aa1 | 3.8% | 91.7% | 2.5% | 1.4% | 0.1% | | | | | | | | | | | | | | | | | 3.8% | 4.1% | 0.00% | 0.4% |
| 1199 | Aa2 | 1.5% | 11.3% | 81.1% | 3.7% | 0.8% | 1.0% | | | | | | | | | | | | | | | | 12.8% | 5.4% | 0.00% | 0.8% |
| 2015 | Aa3 | 0.3% | 3.5% | 7.9% | 80.4% | 4.9% | 1.9% | 0.6% | 0.1% | 0.2% | | | | | | | | | | | | | 11.7% | 7.7% | 0.00% | 0.1% |
| 2390 | A1 | | 0.1% | 1.6% | 7.8% | 77.5% | 9.7% | 2.2% | 0.2% | 0.5% | 0.0% | | | | | | | | | | | | 9.5% | 12.7% | 0.00% | 0.3% |
| 3764 | A2 | 0.0% | | 0.1% | 0.9% | 3.2% | 84.9% | 7.3% | 1.8% | 0.7% | 0.2% | 0.1% | 0.0% | 0.0% | | | | | 0.0% | 0.1% | | | 4.3% | 10.3% | 0.08% | 0.4% |
| 3387 | A3 | 0.1% | 0.1% | 0.0% | 0.2% | 0.9% | 6.2% | 79.8% | 7.4% | 3.6% | 0.9% | 0.2% | 0.1% | | 0.0% | | | | | 0.0% | | | 7.4% | 12.4% | 0.00% | 0.4% |
| 3960 | Baa1 | | 0.1% | | | 0.3% | 1.2% | 5.2% | 80.0% | 9.1% | 2.2% | 0.3% | 0.5% | 0.1% | 0.3% | 0.0% | 0.1% | | | | | | 6.8% | 12.6% | 0.13% | 0.5% |
| 4934 | Baa2 | 0.0% | 0.0% | 0.1% | 0.2% | 0.0% | 0.3% | 1.3% | 5.0% | 82.5% | 7.3% | 0.8% | 0.3% | 0.4% | 0.4% | 0.2% | | 0.2% | | | | | 7.0% | 9.6% | 0.06% | 0.9% |
| 3860 | Baa3 | | | | | 0.1% | 0.2% | 0.5% | 0.7% | 8.7% | 80.4% | 4.5% | 2.1% | 0.8% | 0.4% | 0.2% | 0.2% | 0.1% | | | | | 10.0% | 8.3% | 0.10% | 1.1% |
| 1741 | Ba1 | | | | | | | | 0.6% | 1.7% | 14.2% | 72.1% | 4.5% | 2.2% | 2.1% | 0.7% | 0.3% | | 0.1% | | | | 16.5% | 9.8% | 0.17% | 1.3% |
| 1374 | Ba2 | | | | | | 0.2% | | | 0.2% | 4.7% | 12.5% | 68.3% | 5.8% | 2.0% | 2.3% | 0.7% | | | | 0.1% | | 17.6% | 11.0% | 0.36% | 2.7% |
| 1498 | Ba3 | | | 0.1% | | | | | | | 0.9% | 4.8% | 11.1% | 63.5% | 11.0% | 2.5% | 0.7% | 0.6% | | 0.4% | 0.2% | | 16.8% | 15.4% | 0.67% | 3.6% |
| 2484 | B1 | 0.0% | 0.1% | | | | 0.2% | | | 0.0% | | 0.3% | 2.7% | 7.4% | 69.4% | 9.9% | 2.8% | 0.9% | 0.2% | 0.1% | 0.1% | | 10.8% | 14.0% | 0.56% | 5.2% |
| 4033 | B2 | | | | | | | | 0.0% | 0.0% | | | 0.4% | 1.5% | 6.9% | 69.2% | 8.9% | 4.0% | 0.8% | 0.2% | 0.1% | | 8.9% | 14.0% | 2.90% | 5.1% |
| 2928 | B3 | | | | | | 0.1% | | | | | | 0.0% | 0.3% | 1.5% | 9.9% | 65.2% | 9.2% | 2.4% | 1.7% | 0.4% | | 11.8% | 13.6% | 4.41% | 5.0% |
| 1161 | Caa1 | | | | | | | | | | | 0.3% | 0.1% | 0.1% | 2.3% | 3.4% | 9.6% | 56.1% | 9.6% | 3.0% | 0.3% | | 15.8% | 13.0% | 10.08% | 5.0% |
| 496 | Caa2 | | | | | | | | | | | | 1.0% | | | 0.2% | 5.2% | 13.7% | 48.4% | 1.6% | 2.2% | | 20.2% | 3.8% | 23.39% | 4.2% |
| 159 | Caa3 | | | | | | | | | | | | | | | 0.6% | 1.3% | 1.9% | 5.0% | 36.5% | | | 8.8% | 0.0% | 40.88% | 13.8% |
| 76 | Ca | | | | | | | | | | | | | | | | | 2.6% | 3.9% | 18.4% | 43.4% | | 25.0% | 0.0% | 18.42% | 13.2% |
| 41 | C | | | | | | | | | | | | | | | | | | | 24.4% | | 14.6% | 24.4% | 0.0% | 36.59% | 24.4% |

* One-Year Time Horizon for Bond Data Covering 1/1/99 – 9/1/07

**FAQ 22: What is a ratings gap-conditioned transition matrix?**

Moody's and other major rating agencies have long produced transition matrices. Using historical data, these show how often ratings move, or transition, from one rating category to another, over different time horizons. They also include records of defaults, so thus can be used to determine default rates for different rating categories.

## How does the one-year default rate for B2 rated issuers differ depending on whether they are trading rich or cheap to their ratings?

Existing transition matrices group together issuers of the same rating category in determining transition and default rates.[15] Ratings gap-conditioned transition matrices extend the concept by conditioning default and transition rates on an issuer's implied rating in relation to its Moody's rating. For example, how does the one-year default rate for B2 rated issuers differ depending on whether they are trading rich or cheap to their ratings? The bond dataset is the largest, and contains 182,000 observations.

The transition matrices cover situations of gaps of -6 and below to +6 and above (including gaps of zero), and for all four datasets (bonds, CDS, equities, and MDP). Our most widely referenced transition matrices cover a one-year horizon. We have recently published transition matrices for other time periods (1, 3, 6, 24, and 36 months). Moreover, we have produced them for changes in both Moody's ratings and implied ratings. This makes a total of 624 transition matrices, all of which are available to subscribers on moodys.com. An important point is

*15 However, Moody's has done research that also segments default and ratings change experience by rating outlook. See Hamilton and Cantor (February 2004).*

IV. Applied Research *(continued)*

that the data gets quite thin for large ratings gaps. This would be expected from the distribution of ratings gaps shown in Figure 1. Thus, each row of each transition matrix shows the number of observations (The "Cnt" column in Figure 14), so users can decide for themselves when the data is insufficient to rely on the precise figures in the matrices. Regardless of this, we see consistent patterns of behavior for rich and cheap names. We discuss these in the following sections.

### Default analysis; issuer differentiation

The ability of debt ratings to identify issuers with higher risks of default is well established.[16] That is, issuers with lower ratings generally default at higher rates. The ratings gap-conditioned transition matrices throw a further variable into the mix by calculating different default rates for the issuers with the same Moody's rating depending on their trading levels in the market. See Figure 15 for an example of this.[17]

**Figure 15: One-Year Default Rates Conditioned on Ratings Gaps***

| Moody's Rating | Default Rates 1999-2007 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | All Issuers | Issuers Grouped by their Ratings Gaps | | | | | | |
| | | 3 | 2 | 1 | 0 | -1 | -2 | -3 |
| Baa1 | 0.3% | 0.1% | 0.2% | 0.2% | 0.1% | 0.5% | 0.4% | 0.7% |
| Baa2 | 0.3% | 0.0% | 0.0% | 0.3% | 0.1% | 0.0% | 0.2% | 0.6% |
| Baa3 | 0.4% | 0.0% | 0.1% | 0.0% | 0.1% | 0.6% | 0.6% | 1.3% |
| Ba1 | 0.8% | 0.0% | 0.0% | 0.1% | 0.2% | 0.1% | 0.7% | 0.9% |
| Ba2 | 1.6% | 0.0% | 0.0% | 0.2% | 0.4% | 0.5% | 0.7% | 3.5% |
| Ba3 | 1.0% | 0.0% | 0.0% | 0.1% | 0.7% | 1.0% | 0.8% | 2.2% |
| B1 | 2.4% | 0.4% | 0.1% | 0.2% | 0.6% | 2.5% | 6.6% | 8.2% |
| B2 | 4.7% | 0.2% | 0.6% | 1.1% | 2.9% | 5.7% | 13.1% | 19.7% |
| B3 | 7.5% | 0.7% | 1.8% | 1.3% | 4.4% | 9.8% | 19.9% | 25.7% |
| Caa1 - C | 19.7% | 6.0% | 11.3% | 13.0% | 16.9% | 24.2% | 35.6% | 29.7% |

**Bond dataset*

Let's take the highlighted single-B row as an example. Here we compare the one-year default rate for all single-B rated issuers (4.7%), with that of single-B rated issuers with various implied ratings - that is, with different trading levels. The data covers January 1999 - September 2007. We can see that the more positive the trading level at the beginning of a 12-month period, the lower the subsequent default rate. Issuers with single-B ratings, but that trade in line with the Ba2 credit curve (i.e., the cell in the "3" column), defaulted at only a 0.20% rate, while with Caa2 implied ratings (the cell in the -3 column) defaulted at a 19.7% rate. To put it simply, positive or negative market trading levels at the beginning of a period are subsequently reflected by lower or higher default rates, respectively.

**Positive or negative market trading levels at the beginning of a period are subsequently reflected by lower or higher default rates, respectively**

What lies behind these variations in default experience for entities with the same Moody's rating? It is largely the market's instantaneous reaction to good or bad news concerning the entity, as reflected in its credit spreads and thus in its implied ratings, compared to Moody's more deliberate approach to ratings changes. Thus, at least over relatively short horizons, credit risk professionals can combine an issuer's market trading level and its rating to get a better picture of its average default risk. The offsetting cost is that of higher ratings volatility, and thus more "false signals".

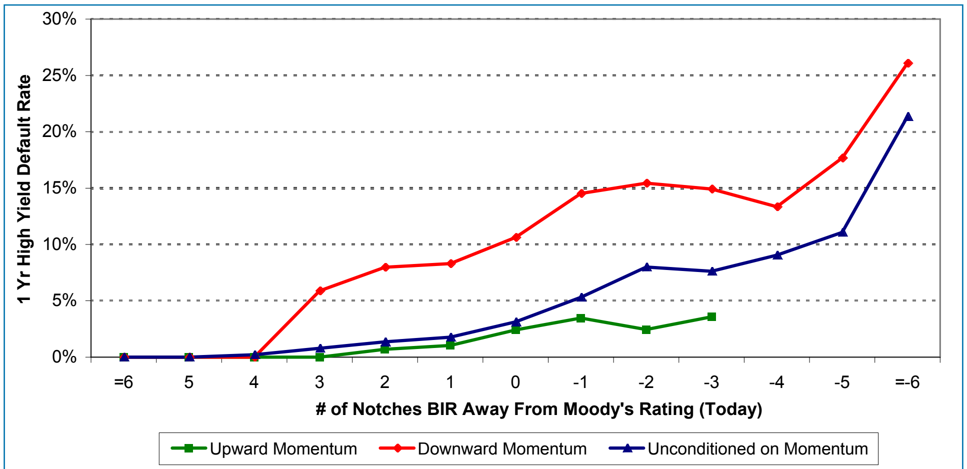
16 *Hamilton and Varma (January 2005).*

17 *Taken from Munves, Jiang and Lam (August 2006), which contains a full review of MIR-based default research.*

### Implied ratings momentum; sharpening the signal still further

In our search for more refined indications of risk we further conditioned our ratings gap analysis on implied ratings "momentum". We defined momentum as a decline in an issuer's implied rating of two or more notches over a three-month period.[18] We found that issuers whose implied ratings exhibited downward momentum subsequently had significantly higher default rates (Figure 16). This is to be expected, since implied ratings are likely to fall sharply due to news on an issuer, news which will often subsequently result in a real event, such as a default. They are to be distinguished from persistent negative gaps that might reflect poor bond trading patterns or industry-wide conditions.

**Figure 16: High Yield Default Rates Conditioned on BIR Momentum* and Ratings Gaps**




** "Momentum" means a BIR change of 2 gaps or more in a positive (upward) or negative (downward) direction in the previous 3 months*

### Using implied ratings to improve estimates of loss-given default

Default is only half the problem faced by credit risk managers. They also worry about loss of asset value post-default, usually expressed as loss-given default (LGD). Better LGD estimation is useful to most credit professionals. There are a variety of ways Market Implied Ratings can help in this regard. For example, Figure 17 shows how MIR data (in the form of ratings gaps) provides better estimates of ultimate recovery for assets with different positions in a firm's capital structure.[19] Such information can lead to greater efficiency in the deployment of capital under the new Basel II regulations governing bank capital requirements.

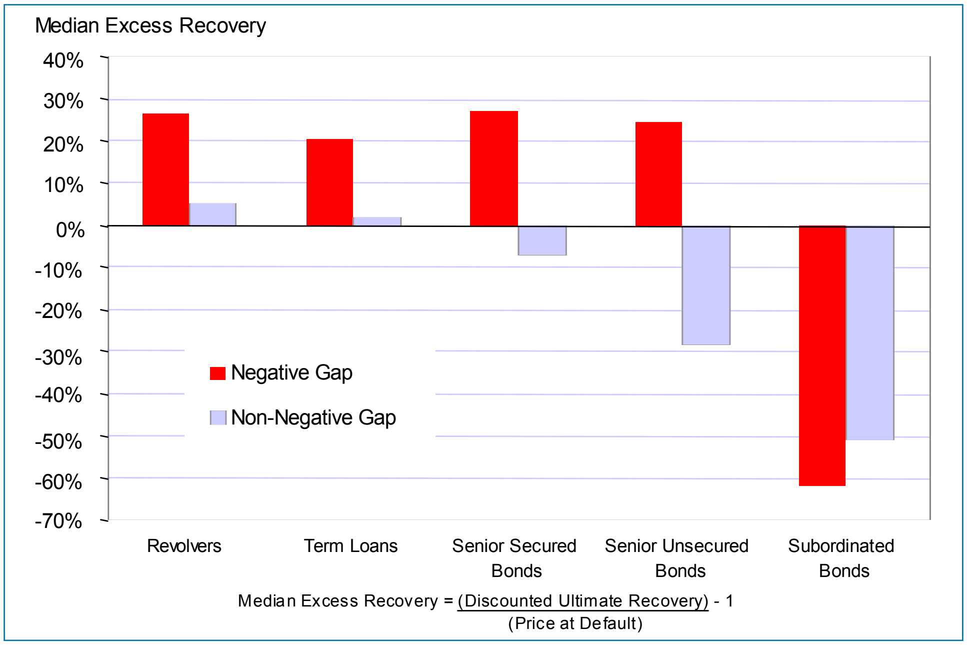
---

[18] *We will shortly be publishing a ViewPoints analysis describing the momentum research.*

[19] *From Hamilton (2007).*

IV. Applied Research *(continued)*

### Figure 17: Median Excess Recovery Rates

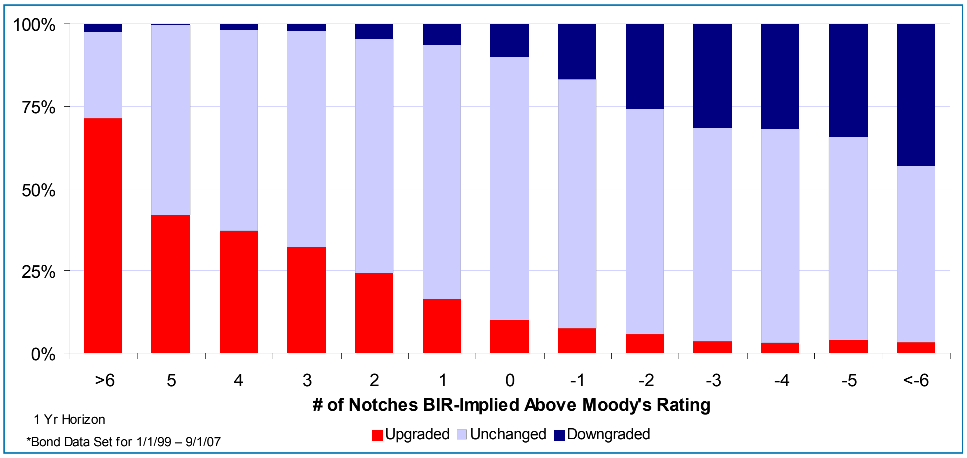



### Ratings change analysis

Figure 18 provides a summary of the ratings gap-conditioned transition matrices discussed above, for the bond dataset. Each bar in the chart summarizes the ratings change experience for all issuers with a given ratings gap state at the beginning of a 12-month cohort period. That is, the bar labeled "0" contains all the issuers where the issuers' implied ratings were in line with their Moody's ratings at the start of a cohort period; the bar labeled "-1" contains all the issuers whose bond-implied rating was one notch below their Moody's ratings. And so on.

From Figure 18 it is evident that the larger the negative ratings gap at the beginning of a 12-month period, the greater is the frequency of future downgrades.[20] The opposite holds for

### Figure 18: Moody's Rating Change Frequency as a Function of the Ratings Gap, One Year Horizon*




[20] *Munves and Jiang (June 2006)*

IV. Applied Research *(continued)*

**The larger the negative ratings gap at the beginning of a 12-month period, the greater is the frequency of future downgrades**

positive ratings gaps. This reflects a simple dynamic. News that significantly affects investors' perceptions of an issuer's future performance is instantaneously reflected in the market trading levels of its securities. This causes a gap to open between the trading level suggested by the issuer's Moody's rating, and the actual trading level. If the news is perceived as bad, then the gap will be negative. In most cases the Moody's analyst responsible for the issuer will also be aware of the news. And if subsequent analysis confirms that it indeed signals a weakening of the issuer's credit standing, then the rating will be lowered. But there is naturally a time lag, and that is what causes the perception, borne out by the data, that Moody's is often "catching up" with the market. Moody's goal of ratings stability, something that has been endorsed over the years by investors, adds to this.

A final note is that we can expect that the worse the news for a company's outlook, the larger the negative gap should be, since the trading levels of its bonds and CDS will be more negatively impacted. This gradation of severity shows up in the greater downgrade rate for issuers with larger negative gaps. From this we can conclude that the Moody's analysts are drawing the same conclusions from the market-implied ratings information.

**FAQ 23: Do implied ratings have relative value applications?**

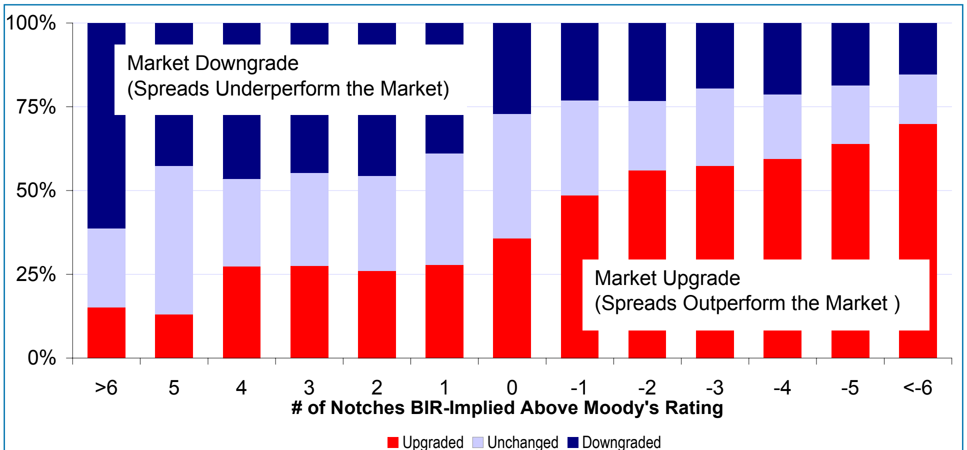
## Relative value analysis

**The Market Implied Ratings data also has relative value applications**

The Market Implied Ratings data also has relative value applications. That is, it can help investors select assets with superior chances of outperforming the broad market (often represented by a bond or CDS index), while identifying those with a greater risk of underperformance. As noted earlier, the key point here is that bond- and CDS-implied ratings are determined with reference to market-wide credit curves, which are updated daily. A general spread widening pushes the curves out, of course. So if an issuer's implied rating falls, it means that its spread has risen by an amount in excess of the general market movement. A rise in an implied rating signals the opposite.

Based on this insight, we can analyze the data to uncover patterns of implied ratings changes, just as we have done for Moody's ratings changes. Figure 19 shows the result.

**Figure 19: Bond-Implied Ratings Changes Conditioned on Ratings Gaps***




**One Year Horizon for BIR Data Covering 1/1/1999 - 9/1/2007*

[20] *Munves and Jiang (June 2006).*

IV. Applied Research *(continued)*

**Implied ratings increase with greater frequency as the ratings gaps become more negative**

As in Figure 18, each bar summarizes the transition matrix for that ratings gap state - the difference is that the changes are for implied ratings (i.e., market trading levels), rather than for Moody's ratings. We can see that the implied ratings increase with greater frequency as the ratings gaps become more negative. The opposite holds for positive ratings gaps. What lies behind these patterns? Let's take the example of the trading pattern of issuers with implied ratings that are below their Moody's ratings. These are viewed as "cheap" by the market, usually because of perceived negative news about the issuers. Often, the market's fears are not borne out. In such cases, investors will buy the cheap assets, causing their prices to increase. This happens at a rate above and beyond the movements of the broad market, and is captured in a rise in the issuers' implied ratings. The opposite happens when the assets become too expensive. Repeating the now-familiar pattern, the greater the gap, the more significant the subsequent move, in this case the change in the relative trading level of the bond or credit default swap. Investors can therefore use Market Implied Ratings to identify overbought and oversold situations for further analysis and action, as appropriate.

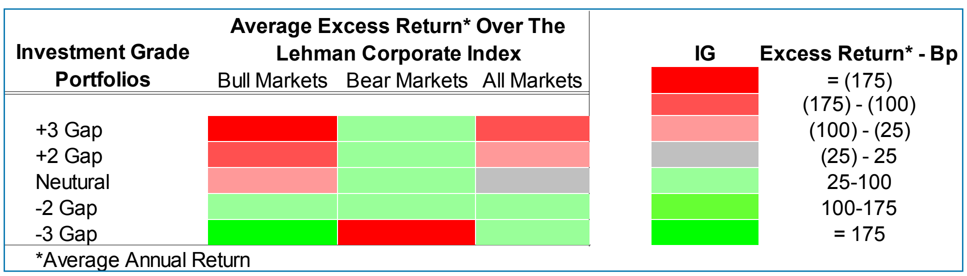
## Portfolio construction and analysis

**How to maximize portfolio returns per unit of risk (i.e., portfolio return volatility) is the main goal of fund managers**

How to maximize portfolio returns per unit of risk (i.e., portfolio return volatility) is the main goal of fund managers. This is well-plowed ground – each fund management group has its own investment process, buttressed by a broad array of quantitative models - but the Market Implied Ratings dataset is new to most investors. Thus, together with the conclusions from relevant analytical studies, the MIR platform provides a fresh way to analyze risk and opportunity.

Figure 20 provides an example of this. It is taken from a study[21] which analyzed the performance of various portfolios, constructed according to ratings gap rules.

**Figure 20: Average Annual Portfolio Performance, 2000 - 2006**




That is, at the beginning of each year in the study period (2000-2006) we formed model portfolios with the all names with a given ratings gap, say -2. These portfolios were then rebalanced to match the quality and duration distribution of the appropriate Lehman Corporate Index (i.e., high grade or high yield). We then calculated the total return on the portfolios vs. the appropriate index. Thus, almost all of the out- or underperformance vs. the relevant market (as represented by the indices) was due to ratings gap-based asset selection. In averaging the results we further separated the performance periods between bull and bear markets. The former are defined as years when the corporate indices outper-

---

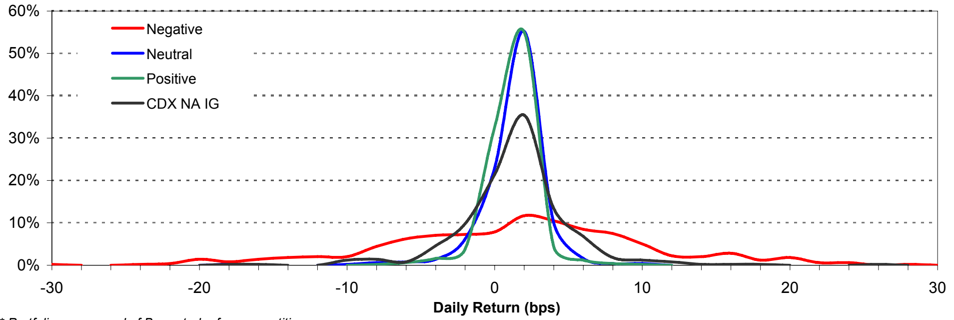
[21] *Love, Munves, and Lam (2007).*

## IV. Applied Research *(continued)*

formed the government markets on a total return basis, while the latter are the years of underperformance. Figure 20 shows that portfolios made up of investment grade entities with bond-implied ratings gaps of -2 outperformed the Lehman Investment Grade Corporate Index on a consistent basis, regardless of market direction. The picture is more mixed for the other ratings gap-based portfolios, with market direction playing strong role in determining which strategies were successful. This is less daunting than it sounds; most portfolio managers have well-formed market views, and construct their portfolios accordingly.

Another portfolio study[22] focuses on questions of asset and portfolio volatility based on ratings gaps. Figure 21 shows the volatility of daily returns of different groups of CDS contracts, grouped by ratings gap.

**Figure 21: Average Portfolio* Return Distribution for Negative, Positive, and Neutral Gap Names vs. CDX IG4-6 Indices**




** Portfolios composed of Baa rated reference entities*

**FAQ 24: Ratings gaps and asset volatility.**

One key finding is that most of the portfolio volatility is concentrated in entities with negative ratings gaps (for purposes of the study, "negative" means gaps of -2 and below). On the other hand, entities with neutral gaps (i.e. CDS-implied ratings gaps of -1, 0, and 1) have approximately the same volatility as positive gap (+2 and above) names, with much higher returns. The beta of the spread on the negative gap portfolio to the spread on the broad market is also much higher than it is for the neutral and positive gap portfolios. None of this is surprising, when we consider the risk signal implied by issuers that trade cheaply for their ratings. Nevertheless, it illustrates how implied ratings can be used to provide new insights into portfolio construction and monitoring.

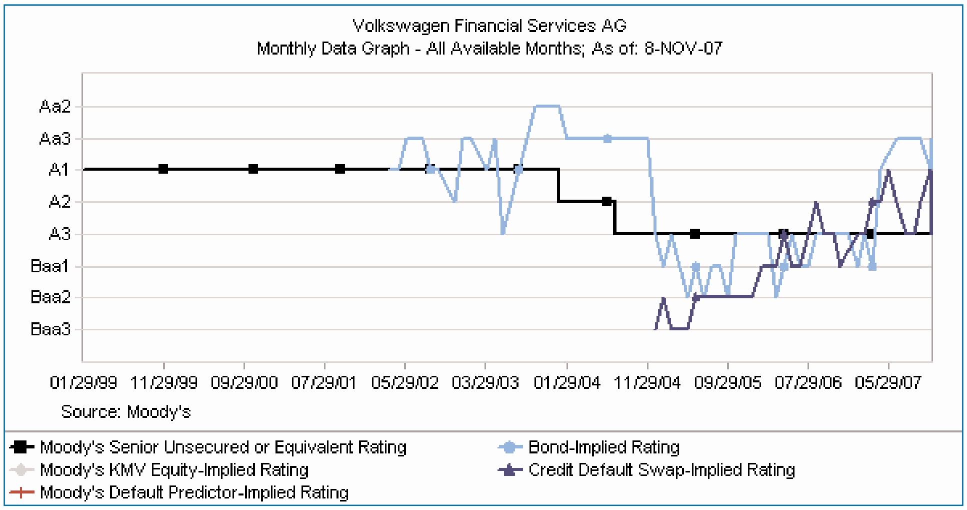
[22] *Jiang, Munves, and Lam (2007).*

**IV. Applied Research** *(continued)*

### Using Market Implied Ratings for asset selection

Last but not least, we consider how investors can use MIR data to aid in their asset selection process. Figure 22 provides one example.

**Figure 22: Volkswagen Financial Services AG**




In the figure we see that Volkswagen's bonds have risen steadily in value over the past few years, to the point that they trade in line with the Aa3 curve, a level three notches above the company's A3 rating, and one not seen since the end of 2004. While some investors might view this as justified, based on the outlook for the company or on market-specific factors, it is undoubtedly expensive compared to recent levels. Supporting this view, the MIR ratings-gap conditioned transition matrices indicate that bonds or CDS of such entities underperform the market around 65% of the time over the next 12 months, while outperforming it with a frequency of only 20%. The rest of the time they perform in line with the market.

# Appendix I: Currency Swap Calculation

## The conversion to U.S. dollars for bonds and credit default swaps

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 in the non-U.S. currency, one uses the standard equation:

$$\text{Price} = \frac{100}{(1+y)^T} + \sum_{coupons} \frac{c}{(1+y)^t} \quad \text{(A1)}$$

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

$$S_0 \ \text{Price}_{U.S.} = \frac{100\, F_T}{(1+y_{US})^T} + \sum_{coupons} \frac{c\, F_t}{(1+y_{US})^t} \quad \text{(A2)}$$

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.

$$\frac{F_t}{S_0} = \left( \frac{1+r_{US,t}}{1+r_t} \right)^t \quad \text{(A3)}$$

Combining the previous terms, if interest rate curves are flat, the yield in non-U.S. currencies is related to that in the U.S. currency by

$$1 + y_{US} = (1+y) * \frac{1+r_{US}}{1+r} \quad \text{(A4)}$$

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 (A4) directly. The swap rates assume an exchange of fixed cash payments and so it is only the existence of the principle payment at maturity that requires an assumption of flat interest rate term structures.

The two main advantages to this method are (1) it allows us to use the relatively more reliable swap rate quotes instead of interest rate quotes and (2) 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 U.S. interest curve is rising faster (slower) with maturity than the foreign curve, our estimate will be slightly low (high). This bias has typically been a few basis points at most.

# Appendix II: Deriving Moody's Issuer Level Senior Unsecured Ratings or their Equivalent

The Senior Ratings Algorithm (SRA) lies at the heart of the process of determining an issuer's MIR senior unsecured rating or equivalent

An issuer's senior unsecured rating or its equivalent 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

The Senior Ratings Algorithm (SRA) lies at the heart of the process of determining an issuer's MIR senior unsecured rating or equivalent.[23] The SRA operates as a two-step process for a given issuer. The steps are (1) the selection of the **reference rating**; and (2) the **transformation** of the reference rating into the issuer's unsecured or equivalent rating. This transformation is achieved through the process of **notching**.[24]

## Reference rating selection

We first tackle the identification of the **reference rating**. The reference rating can be a debt obligation rating or an enterprise level rating (such as a corporate family rating). For each issuer, we consult a priority table to determine its highest ranked rated debt issue or enterprise level rating. Please see Figure 1 for the current table. As its name suggests, the table prioritizes obligation and enterprise level ratings by their class and seniority. Observant readers will note that the priority ranking in Figure 1 does **not** follow the order of priority in a typical issuer's capital structure. Readers will also note that the priority options the table include different types of ratings – issuer ratings, corporate family ratings (CFRs), and bond level ratings.

For example, let's take a high yield issuer with a senior unsecured bond rating and a corporate family rating. According to Figure 1, the senior unsecured rating (Priority 2) would become the reference rating, rather than the Corporate Family Rating (Priority 7). This highlights a common area of confusion regarding "reference ratings", as the term is used in the Senior Rating Algorithm; **the reference rating for the SRA is not necessarily the benchmark Moody's rating associated with an issuer**. Since our example involves a high yield issuer, the **benchmark rating** would be the corporate family rating, which is distinct from the senior unsecured rating providing the reference rating.

The foregoing paragraphs cover the main points around the determination of the reference rating, and suffice for most issuers. But for the sake of completeness, there are two other aspects of determining reference ratings that deserve mention.

*23 For details on the SRA methodology, see Hamilton (July 2005).*

*24 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*

**Appendix II** *(continued)*

The first concerns situations where the highest ranking debt class is issue-based, and there is more than one security in it. In that case we need to determine which single issue will become the **reference bond**. We do so by applying the following rules:

- Bonds without backing by other entities receive higher priority
- Bonds with only one issuer (i.e. without joint responsibility for the obligation from two or more entities) receive higher priority
- The lowest rated issue in the asset class receives higher priority
- Finally, if the selection cannot be made on the foregoing three criteria, then an issue within the highest ranked debt class is selected at random

**FAQ 27: Do we use domestic or foreign currency ratings?**

A second issue concerns domestic vs. foreign currency ratings. In some cases, the SRA calls for the calculation of two rating histories for each issuer, one using foreign currency ratings and one using domestic currency ratings. Foreign currency ratings receive the highest priority and are most often used. However, in order to derive as long a rating history as possible, domestic currency ratings are used for emerging market issuers when necessary.[25]

### Figure 1: Priority Rankings for Reference Obligations or Enterprise Levels

| Priority | Debt Class | Priority | Debt Class |
|---|---|---|---|
| 1 | Issuer Ratings | 9 | Subordinated Bond Ratings |
| 2 | Senior Unsecured Bond Ratings | 10 | Junior Subordinated Bond Ratings |
| 3 | Senior Unsecured MTN and Shelf Ratings | 11 | Senior Secured Bond Ratings |
| 4 | OSO Ratings | 12 | Senior Secured Loan Ratings |
| 5 | Insurance Financial Strength Ratings | 13 | Security Deposit Ratings |
| 6 | Senior Unsecured Loan Ratings | 14 | Bank Note Ratings |
| 7 | Corporate Family Ratings | 15 | Preferred Stock Ratings |
| 8 | Senior Subordinated Bond Ratings | | |

### Step 2; determining the senior unsecured rating by notching from the reference rating

Once the reference bond or asset class is determined (its Moody's rating is already known, of course), the second step is to calculate the issuer's senior unsecured equivalent rating from the **Senior Unsecured Ratings Lookup Matrix**, shown in Figure 2. The matrix reflects the process of notching from the reference rating in order to arrive at the issuer's senior unsecured rating.[26]

To start with the obvious, senior unsecured bond ratings require no notching, since we are seeking to determine an issuer's senior unsecured rating. Similarly, as they represent a firm's senior unsecured credit risk, issuer ratings are not adjusted either. Other reference ratings, which reflect expected differences in loss given default due to their position in a firm's capital structure or collateral, must be notched either up or down. Let's take one example of each situation.

*[25] Differences between foreign and domestic currency ratings have diminished since 2001 when Moody's began to loosen its sovereign ceiling ratings policy. See Levey and Truglia (June 2001).*

*[26] Before 2000, the Moody's notching table was built based on judgmental experience. Since 2000, Moody's has revised the methodology to determine the notching magnitude in terms of the relative expected loss of individual debt with respect to the benchmark debt. For detailed notching guidelines, readers are referred to the following Special Comments:*

- *Notching for Differences in Priority of Claims and Integration of the Preferred Stock Rating Scale, November 2000.*
- *Summary Guidance for Notching Secured Bonds, Subordinated Bonds, and Preferred Stock of Corporate Issuers, September 2001.*
- *Updated Summary Guidance for Notching Bonds, Preferred Stocks and Hybrid Securities of Corporate Issuers, February 2007.*

## Appendix II *(continued)*

As our notching up example, assume that the only rating an issuer has is a Baa1 subordinated obligation. To derive this issuer's senior unsecured equivalent rating, we first find the Baa1 rating in the first column, then read across the table to the Sr. Subordinated/Subordinated column. Doing this we see that the subordinated bond rating is notched up to the senior unsecured equivalent rating of A3. (Perhaps confusingly, the Sr. Unsecured column is **not** the correct one to which to refer.)

### Figure 2: Senior Unsecured Ratings Lookup Matrix

| Rating of Reference Security | Sr. Secured / Equipment Trust (EQT) | Sr. Implied / IFSR (SS / SI / CLM) | Sr. Unsecured / MTN (SIJ) | Sr. Subordinated / Subordinated (SR/SB | Jr. Subordinated / Jr. Unsecured (JS) | Preferred Stock (PPF) |
|---|---|---|---|---|---|---|
| Aaa | Aa2 | Aa1 | Aaa | Aaa | Aaa | Aaa |
| Aa1 | Aa3 | Aa2 | Aa1 | Aaa | Aaa | Aaa |
| Aa2 | A1 | Aa3 | Aa2 | Aa1 | Aa1 | Aaa |
| Aa3 | A2 | A1 | Aa3 | Aa2 | Aa2 | Aa1 |
| A1 | A3 | A2 | A1 | Aa3 | Aa3 | Aa2 |
| A2 | Baa1 | A3 | A2 | A1 | A1 | Aa3 |
| A3 | Baa2 | Baa1 | A3 | A2 | A2 | A1 |
| Baa1 | Baa3 | Baa2 | Baa1 | A3 | A3 | A2 |
| Baa2 | Ba1 | Baa3 | Baa2 | Baa1 | Baa1 | A3 |
| Baa3 | Ba2 | Ba1 | Baa3 | Baa2 | Baa2 | Baa1 |
| Ba1 | Ba3 | Ba2 | Ba1 | Baa3 | Baa3 | Baa2 |
| Ba2 | B1 | Ba3 | Ba2 | Ba1 | Ba1 | Baa3 |
| Ba3 | B2 | B1 | Ba3 | Ba2 | Ba2 | Ba1 |
| B1 | B3 | B2 | B1 | Ba3 | Ba3 | Ba2 |
| B2 | Caa1 | B3 | B2 | B1 | B1 | Ba3 |
| B3 | Caa2 | Caa1 | B3 | B2 | B2 | B1 |
| Caa1 | Caa3 | Caa2 | Caa1 | B3 | B3 | B2 |
| Caa2 | Ca | Caa3 | Caa2 | Caa1 | B3 | B3 |
| Caa3 | C | Ca | Caa3 | Caa2 | Caa1 | Caa1 |
| Ca | C | C | Ca | Caa3 | Caa2 | Caa2 |
| C | C | C | C | Ca | Caa3 | Caa3 |

Now let's review an example where a reference rating is notched down. Here we'll take an issuer with senior secured rating of B1. This becomes the reference rating in the first column of Figure 2. The next column to the right, headed Sr Unsecured/Equipment Trust is the relevant one for the lookup. The rating here is B3, and this becomes the issuer's senior unsecured or equivalent rating.

The Fiat sidebar provides an illustration of some of the complexities that can arise in practice around notching. It also shows how the senior unsecured or equivalent rating per MIR can vary from the Moody's rating that is most commonly associated with an issuer.

### Fiat: MIR Ratings vs. Moody's Ratings

Fiat provides an example where a senior unsecured or equivalent Moody's rating in MIR can differ from the most commonly referenced Moody's rating.

Fiat S.p.A. (the group's holding company) has a Corporate Family Rating of Ba1. This is generally considered to be Fiat's "benchmark rating". However, Fiat S.p.A.'s senior unsecured or equivalent rating in MIR is Ba2. This is because the entity has no senior unsecured debt rated by Moody's. Its highest priority rating per Figure 1 is the CFR, at number 8. Since the company's CFR is Ba1, its senior unsecured or equivalent rating is notched down one rating category from that, or Ba2. This can be derived from Figure 2, where a Ba1 rating in the "Rating of Reference Security" column equates to a Ba2 rating in the "Senior Implied" column (third from the left).

The Fiat group's Ba1 rated debt is issued by Fiat Finance & Trade (F&T), with a guarantee from Fiat S.p.A. F&T's "senior unsecured or equivalent" rating is Ba1. This reflects the priority rankings in Figure 1, where senior unsecured (domestic) ratings have highest priority. So for the Fiat group the "senior unsecured or equivalent rating" for a subsidiary is lower than for its parent.

# Appendix III: Calculation of Bond-implied Rating Median Credit Spreads and Credit Curve Construction

## Calculating option-adjusted spreads

Approximately five 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 the embedded options on the bonds yield. 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 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 ratings-based groups, or buckets. The groups 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.[27] The medians focus the results on representative (median) observations, while the curve-fitting process smoothes the output.[28]

For each bucket we begin the curve-building process by taking the 51 securities with the shortest durations. From this we obtain a single datapoint, or observation, which represents the median spread (on the Y axis of the curve graph) and the median duration (plotted on

*27 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.*

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

Appendix III *(continued)*

the X axis). We then drop the shortest duration bond and add the next longest duration bond, and calculate a second observation. The process is repeated, moving out the duration curve, until we have included all the bonds in the group, except the 25 with the shortest durations and the 25 with the longest durations.

In some instances we have found that the ratings-based buckets are thinly populated, and the small number of bonds means that we end up with fewer than 100 total observations. In such cases the small number of observations means that the credit curve for the bucket is not well estimated. So we take an alternative approach to plot the curve, one using a non-linear regression.

A final note is that we have experimented with different observation group sizes (i.e., bigger and smaller than 51 bonds), and the results were unaffected. We have also experimented with requiring issuers to only appear once in each 51-security group, but the results were also unaffected.

We have to make a further adjustment for the buckets that represent broad rating categories. For them, we need to take into account the breakdown of a bucket's population by alphanumeric rating category. Let's take the Aa bucket as an example, and assume that one 51-bond duration-based group has 10 Aa1s, 11 Aa2s, and 30 Aa3s. In other words, it's overweight Aa3 rated entities. In this case we would use the 16th observation, which corresponds to the mid-point of the three fine rating category samples, rather than the 26th observation, which would be the standard median.

Finally, we must address how we derive curves for alphanumeric rating categories (e.g., A1, A2, A3) when we have only calculated curves for a broad rating category (e.g., single-A). In such cases, we interpolate the alphanumeric curves using an exponential formula. For example, to determine the A3 curve, we would use the formula

$$Ln(A3) = 2/3\ Ln(A2) + 1/3 Ln(Baa2)$$

We use natural logs because the distance between credit curves grows exponentially as you move down the credit spectrum.

### Curve transformations and refinements

The power curve has two degrees of freedom and provides for upward or 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. The equation for a power curve is:

$$Spread = \beta\ Duration^{\alpha}$$

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

$$Ln(Spread) = Ln(\beta) + \alpha\ Ln(Duration) + \varepsilon$$

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

## Appendix III *(continued)*

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( )* is constrained to be a certain distance higher than that of the previous curve and 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.

# VIII. References


Crosbie and Bohn (2003), "Modeling Default Risk" (Moody's KMV publication)

Fons, J.S., Viswanathan, J., (December 2004), "A User's Guide to Moody's Default Predictor Model: An Accounting Ratio Approach", (Moody's Special Comments, Global Credit Research, Moody's Investors Service)

Fons, J., Woolley, M., (June 2007), "Moody's Default Predictor: An Update", Moody's Special Comments, (Global Credit Research, Moody's Investors Service)

Dwyer, D., and Qu, S. (2007), "EDF 8.0 Model Enhancements" (Moody's KMV publication)

Hamilton, D. T., (July 2005) ,"Moody's Senior Ratings Algorithm & Estimated Senior Ratings", (Global Credit Research, Moody's Investors Service)

Hamilton, D. T., (2007) ,"Using Market Implied Ratings to Enhance Recovery in Default", (ViewPoints publication, Moody's Credit Strategy Group)

Hamilton, D. T., Cantor, R. , (February 2004), "Rating Transitions and Defaults Conditional on Watchlist, Outlook and Rating History," (Global Credit Research, Moody's Investors Service). Republished in Hamilton, D. T., Cantor R.,( September 2004), "Rating Transition and Default Rates Conditioned on Outlooks," (Journal of Fixed Income)

Hamilton, D. T., Varma, P., (January 2005), "Default and Recovery Rates of Corporate Bond Issuers," (Global Credit Research, Moody's Investors Service)

Korablev, I., and Dwyer, D. (2007), "Power and Level Validation of Moody's KMV EDF Credit Measures in North America, Europe, and Asia" (Moody's KMV publication)

Levey, D., V. Truglia, (June 2001) "Revised Country Ceiling Policy", (Global Credit Research, Moody's Investors Service)

Love, M., Munves, D., and Lam, C. (July, 2007),"Bond-Implied Ratings: A New Framework for Portfolio Optimization", (ViewPoints publication, Moody's Credit Strategy Group)

Munves, D., and Jiang, S. (June, 2006), "Ratings Gaps Across Models and Their Significance in Ratings Change Analysis", (Moody's Credit Strategy Group).

Munves, D., Jiang, S., and Lam, C. (August, 2006), "Ratings Default Rates Conditioned on Market Implied Ratings; A Cross-Model Analysis" (Moody's Credit Strategy Group publication)

# IX. Frequently Asked Questions

Report Number: 106083

**Authors**

David W. Munves, CFA
David T. Hamilton, Ph.D.

**Production Specialist**

Yelena Ponirovskaya