Special Comment

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The Effectiveness Of Credit Ratings As Indicators Of Relative Industry Default Risk

This special comment examines the ability of various indicators to anticipate three-year cumulative default rates by industry. We explore alternative ways to use credit ratings to assess relative default risk among industries and compare the predictive power of ratings-based metrics with that of common financial metrics and market-implied risk assessments. We also examine whether simple composite indexes formed over several indicators increase predictive power. Our primary findings are:

- Relative industry default rates fluctuate substantially over time; therefore, good industry risk indicators should also be dynamic.
- The power of "average" rating levels as indicators of subsequent relative default rates varies and depends on the way that the average is calculated. The most effective ratings-based measure, which we term the *adjusted ratings-implied expected default rate*,
  - adjusts individual company ratings up by one alpha-numeric rating notch for a positive outlook and down a notch for a negative outlook,
  - adjusts individual company ratings up by two alpha-numeric rating notches for a positive rating review (watchlist) or down two notches for a negative rating review, and
  - averages these adjusted ratings by industry on a weighted basis, where the weights correspond to each rating category's expected three-year default rate.
- The adjusted ratings-implied industry default rate has been more effective than standard financial metrics – such as industry average (or median) leverage or coverage ratios – and industry average market-implied ratings in anticipating relative default rates. Of the financial indicators we test, the median leverage ratio of firms within each industry proves the most useful.
- Simple composite indexes that combine financial and market-implied data with ratings information have outperformed the simple ratings-based metrics alone.

These results must be interpreted with care. The concept of industry risk studied here – specifically, default risk – is distinct from any notion of inherent or intrinsic industry risk. In particular, highly leveraged issuers in an "intrinsically safe" industry might pose a greater risk of default than an issuer with very low leverage in an "intrinsically risky" industry. Rather than try to identify intrinsic risk, this paper examines the power of various indicators to anticipate industry default rates conditional on the financial policies and corporate strategies of firms within each industry.

Moody's Investors Service
Global Credit Research

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I. Introduction

The power of Moody's ratings to indicate relative credit risk at the issuer level is well established.[1] It is reasonable to expect that ratings should also be informative of relative credit risk at higher aggregations, in particular at the industry level. Knowing that issuers in one industry are currently rated lower than issuers in another industry should indicate greater credit risk as a whole in the "lower rated" industry.[2]

The practical problem for investors wishing to use Moody's ratings for such comparisons is that different industries have different distributions of ratings. It is not obvious how to use the information on 100 rated issuers in the Aerospace & Defense industry to form an opinion of credit risk relative to the 176 rated issuers in the Media & Entertainment industry. This leads to the first objective of this study: to formulate a summary statistic of an industry's ratings distribution that will permit a meaningful comparison of relative credit risk across industries.

Of course, the key here is that the comparison should be *meaningful* – that is, the comparison should have some predictive power. The second objective is thus to evaluate the effectiveness of a metric in discerning relative industry risk. This is a different problem from the usual one of trying to identify when default rates may be expected to rise or fall. Even in periods of generally low default rates, some industries will be at greater risk for default than others. Our task is to find indicators that correctly discern the higher risk industries from the lower risk ones under all market and credit conditions.

We can employ various standards of effectiveness against our metrics. At a minimum, our metrics should correctly rank-order industries. However, an ideal measure of relative risk would also permit us to say something about the *magnitude* of the difference between two industries. We will generally assess our proposed indicators by this higher standard.

Finally, we want to know whether some non-ratings based signals might also be effective in making these comparisons. We thus consider several key financial measures as indicators of relative industry default risk. Perhaps surprisingly, several financial measures that are very powerful in anticipating changes in aggregate default rates over time prove ineffective in ranking relative risk at a specific point in time. We also consider market-implied rating models as predictors of relative default risk. We find that, historically, these have been less effective than Moody's ratings have been.

It is also possible to use available data to form composite indexes that combine ratings-based indicators with financial indicators. These simple composites have been slightly more effective than ratings-based indicators alone, which suggests the possibility that there may be important gains from constructing a well-specified empirical model of relative industry default risks. However, a rigorous exploration of this approach is beyond the scope of this study.

This Comment is organized as follows. The underlying data and methodology are discussed in Section II. Section III. explores the history of defaults at the industry level, and how fluid the relative ranking of three-year default rates has been. Section IV. presents several Moody's ratings-based metrics as candidate indicators of relative default risk among industries and tests their predictive power, while Section V. focuses on our recommended metric for assessing this relative risk: the adjusted ratings-implied expected default rate. Section VI. similarly tests several financial ratios commonly used in credit analysis. Market-implied and financial statement-implied ratings models are tested in Section VII., while Section VIII. explores some simple composite indexes formed over sets of all these candidate indicators. Section IX. concludes.

1. *See, e.g., Hamilton et al (2004).*
2. *We mean greater risk conditional on the current financial status of the constituent issuers. It is not intended to be a statement of "inherent" business risk.*

II. Data and Methodology

For the purpose of this Special Comment, an industry is defined as an aggregation of issuers that share either common demand or supply drivers. As such, it is a fundamental business concept, as opposed to a credit-risk concept. Exhibit 1 lists the industries studied herein. Industry assignments are based on Moody's assignments of broad and specific industry classifications.

Exhibit 1 **Industry Coverage**

Aerospace & Defense	Leisure
Agriculture/Food & Beverage	Media & Entertainment
Automotive	Metals & Mining
Capital Goods	Oil & Gas
Chemicals, Packaging & Environmental Services	Retailing
Consumer Products	Services
Forest Products & Basic Materials	Telecommunications
Healthcare	Transportation
High Technology	

Our study of "credit risk" is restricted to the cumulative three-year default rate, though our results are robust to shorter and longer horizons. In other words, the risk of an industry as of 2000q1 will be measured ex-post by the default rate from 2000q2 through 2003q1, inclusive.

This study uses data from several sources. From Moody's proprietary ratings database, we use the estimated senior unsecured rating on corporate bond issuers from the United States and Canada. Sovereign and municipal debt issuers, as well as structured finance transactions, private placements, and issuers with only short-term debt, are excluded from the study. We sample the data quarterly, such that the rating attributed to a given quarter is the rating that was assigned on the last day of the quarter. The data set covers 1982q2 through 2004q1, inclusive. We allow the sample to change with issuer entry and exit. In the industries studied in this report, there are on average 1,400 issuers active in any given quarter, ranging from a low of 840 issuers in 1982q2 to a high of 2,085 in 1999q4. In 2004q1, there were 1,758 issuers active in the industries we study. It is often, but not always, the case that default coincides with the withdrawal of the rating; for this study, we drop defaulted issuers from the sample even if a rating is maintained. All historical measures are issuer-weighted, as opposed to dollar volume-weighted.

Default data are taken from Moody's proprietary default database. Briefly stated, defaults are defined as one of three credit events: missed or delayed interest or principal payments; bankruptcy or receivership; or a distressed exchange to diminish the financial obligation of the issuer.[3] Default rates are defined simply as the ratio of the number of defaulting issuers in a given quarter to the number of active issuers in that quarter.

Financial data are taken from Compustat and held fixed for the subsequent four quarters. We assume equivalence between fiscal and calendar years.

Different metrics are compared by their utility in discriminating subsequent three-year default rates by industry. As a concrete example, consider the most obvious summary measure of the ratings distribution: the simple mean rating. This metric can be calculated for each industry at any point in time based on the distribution of issuer ratings within that industry at that point in time. When compared across industries, this metric will imply a certain rank-order of industries. This rank-order can then be compared with the rank-order given by the subsequent three-year default rate.

While a good indicator will correctly rank-order industries, an ideal indicator will also provide some quantitative implication of relative credit risk. If it is good to know that "industry A is riskier than B," it is better to know *by how much* the risk in A exceeds that of B. We will thus evaluate our metrics not only by whether they imply the correct rank-order, but by whether they imply the correct relative values.

Consider a concrete example. From 2001 through 2004, the five industries with the lowest default rates were: Oil & Gas (standardized value[4] 98.46), Forest Products & Basic Materials (98.93), Healthcare (98.96), Agriculture/Food & Beverage (99.13) and High Technology (99.52). Suppose that our first candidate indicator yields the normalized values {98.5, 99, 99.5, 100, 100.5} for these five industries as of the beginning of 2001. On the one hand, this indicator would have given us the perfectly correct rank-ordering. But, on the other hand, it implies that the difference in default risk between the Oil & Gas and the Forest Products industries is the same as the difference between the Forest Products and Healthcare industries, when in fact Forest Products and Healthcare had essentially identical default rates from 2001 through 2004. That these industries can be ranked "2nd" and "3rd" belies the fact that there was really no meaningful difference in their cumulative three-year default rates.

3. *Please see Keenan and Hamilton (2002) for a thorough discussion.*
4. *By "standardized" we mean simply that the data have been linearly transformed to mean 100, standard deviation 1.*

Compare that with a second hypothetical indicator, which as of the beginning of 2001 yields normalized values {98.5, 99, 98.9, 99.1, 99.5}. This indicator does not correctly rank-order the five industries, but it does correctly indicate that the default rate for the Oil & Gas industry will be much lower than for all the others, that the default rate for the High Technology industry will be much higher than for all the others, and that the default rates for the remaining three industries will be clustered very closely together.

For some purposes, one indicator might be more useful than the other. Throughout this study, we will distinguish correlations on a rank-order basis from correlations on an index-value basis.

III. Default History

Exhibit 2 reports summary statistics of the default experience of the different industries since 1982q2, including the mean default rate, standard deviation of default rates, the correlation with the aggregate default rate, and the Beta to the aggregate default rate. Each of these could correspond to a different notion of "risk" – either high rates of default on average, variable (and thus presumably, though not necessarily, less predictable) rates of default, or defaults which strongly correlate with aggregate default risk.

Exhibit 2

Summary Statistics of Industry Default Experience
From 1982q2 through 2004q1

			To Aggregate Default Rate	
Industry	**Mean**	**St Dev**	**Correlation**	**Beta**
Aerospace & Defense	2.2	6.4	0.34	1.24
Agriculture/Food & Beverage	1.7	2.9	0.41	0.69
Automotive	2.7	5.6	0.38	1.24
Capital Goods	2.3	3.5	0.68	1.36
Chemicals, Packaging & ES	1.7	3.2	0.55	1.01
Consumer Products	4.0	5.3	0.70	2.13
Forest Products & BM	1.8	4.9	0.49	1.40
Healthcare	3.1	5.6	0.52	1.65
High Technology	2.8	4.4	0.22	0.56
Leisure	5.1	10.3	0.44	2.61
Media & Entertainment	3.5	4.8	0.59	1.61
Metals & Mining	4.0	7.9	0.35	1.57
Oil & Gas	2.1	3.9	0.10	0.22
Retailing	3.7	5.7	0.39	1.26
Services	3.5	10.6	0.13	0.78
Telecommunications	2.1	4.4	0.35	0.89
Transportation	2.0	3.3	0.55	1.06

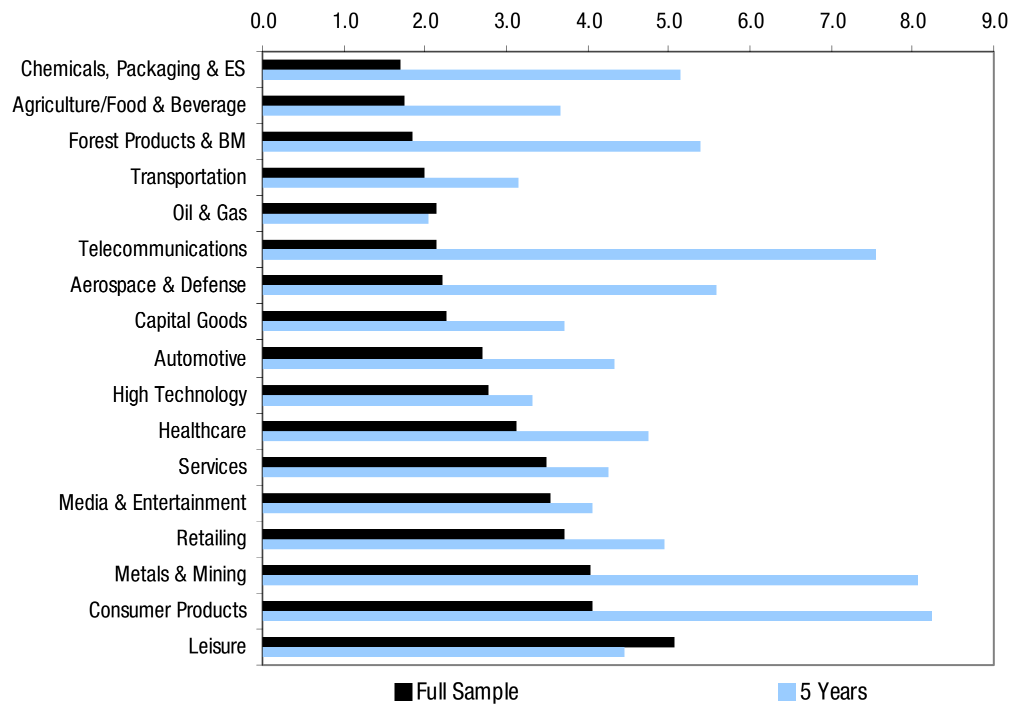
Source: Moody's database as of March 31, 2004

Exhibit 3 takes the average default rate over the period 1982q2 through 2004q1 (as reported in Exhibit 2) and compares it with the average default rate of the last five years. What interests us is not just that the default rates are different, but that the relative ranking of default rates is different. The Chemicals, Packaging & Environmental Services industry has the lowest average default rate over the entire sample, but the 12th highest in the last five years. The default rate of the Oil & Gas industry has been stable in an absolute sense, but its relative ranking changes from 5th in the full sample to 1st in the five-year sub-sample. The implication is that any metric which purports to correctly summarize relative default risk across industries must be fairly dynamic, for relative risk changes over time.

Exhibit 3

Average Default Rates

Comparing the average of 1982q2 – 2004q1 with the average of 1999q2 – 2004q1



Source: Moody's database as of March 31, 2004

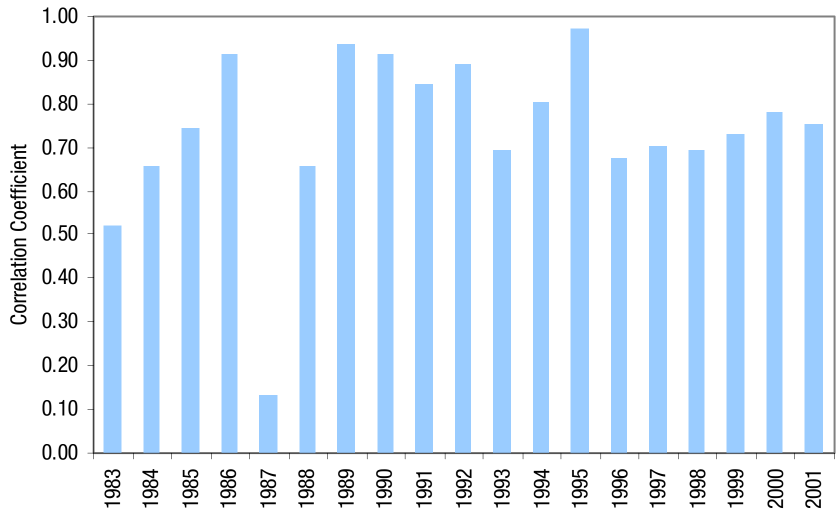
How dynamic does it have to be? Exhibit 3 demonstrates that relative rankings change, but perhaps they change "slowly." To test this, define the cumulative three-year default rate as of, for example, 1982q1 to be the default rate from 1982q2 through 1985q1, inclusive. Having calculated these cumulative rates for 1982q1, 1983q1, and so on through 2001q1, rank-order the cumulative rates for each year. Then calculate the (rank-order) correlation from one year to the next. That is, define the correlation for 1983 to be the correlation of the rank-order of cumulative default rates from 1983q1 with that of 1982q1.

It is reasonable to expect a good deal of persistence when moving from one year to the next, in other words, to expect high correlations over consecutive rank-orders. After all, the cumulative rate as of 1982q1 includes defaults from 1982q2 through 1985q1, and the cumulative rate as of 1983q1 covers defaults from 1983q2 through 1986q1. Exhibit 4 reports these correlations. They are surprisingly low (only 0.74 on average) ranging from a maximum of 0.97 in 1985 to a minimum of 0.13 in 1987. In other words, if we had known with certainty the relative rank of the future three-year default rates as of 1986, that information would have been of almost no use in 1987.

Exhibit 4

Rank-Order Correlations

Comparing the rank-order of three-year default rates from one year to the next



Source: Moody's ratings database as of March 31, 2004

The fluid nature of relative default risk can be demonstrated another way. Most industries have, at one time, been ranked either 1st or 2nd, and, at another time, ranked either 16th or 17th out of the 17 industries. Even the Agriculture/Food & Beverage industry, which has the lowest standard deviation of default rates in this sample, has at one time been ranked 2nd and at another time 13th. One cannot dismiss some industries as always low risk for default and others as always high risk. Every industry has been both at different times over the last twenty years.[5]

The objective of this study is to test different candidate indicators in their ability to correctly anticipate relative default risk.

IV. Summary Statistics of the Moody's Ratings Distribution

Moody's does not assign ratings to industries. The question then becomes how to aggregate the ratings assigned to individual issuers to form an opinion of that industry's credit risk? In short, we want to find out what is the most meaningful way to summarize an industry's entire ratings distribution for the purpose of anticipating three-year default rates.

Several possibilities suggest themselves. The most obvious is to take the mean (or median) rating in an industry. That is, assign values to the alpha-numeric rating codes (e.g., Aaa = 1, Aa1 = 2, and so on) and compute the arithmetic average of the issuers comprising an industry. Another possibility might be to calculate the share of issuers with ratings below certain thresholds (e.g., the share with spec-grade ratings, or the share rated Caa1 or below). One could also examine summary statistics beyond the mean or median, such as the dispersion of ratings, or the skewness of the ratings distribution within an industry.

Each of these approaches (and others besides) is reasonable on its face, and most have done a reasonable job of ranking industries in the past. However, another summary statistic – the adjusted ratings-implied expected default rate – dominates these other measures. This metric, described in detail below in Section V., represents the best use of the ratings distribution to summarize default risk at the industry level.

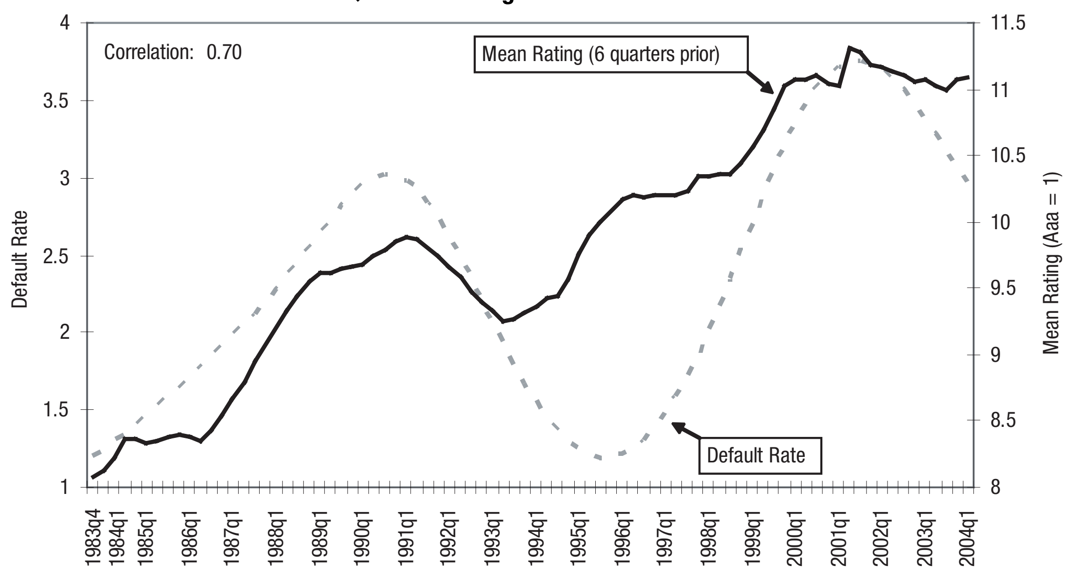
5. *These changes in default risk do not necessarily reflect changes in the intrinsic risk of an industry.*

We first consider the mean rating of an industry as a summary statistic for relative credit risk, assuming a linear rating scale. At any point in time, we can calculate this mean rating given the distribution of issuer ratings within an industry. Presumably, if the average rating of the issuers in industry A is better (numerically lower, if we start arbitrarily with Aaa = 1) than that of B, then we could say that credit conditions in A are, on average, better (safer) than those of B.

Exhibit 5 plots the aggregate default rate (smoothed by a center-weighted algorithm) and the aggregate mean rating (that is, the mean rating of the entire sample without regard to industrial classification) lagged six quarters.[6] Evidently, in the aggregate, the mean rating has been a useful indicator of the aggregate default rate trend, even though this is not the stated purpose of Moody's ratings.

Exhibit 5 **Aggregate Default Rate and Aggregate Mean Rating (Aaa = 1)**

6 Quarter Leading Correlation of 0.70



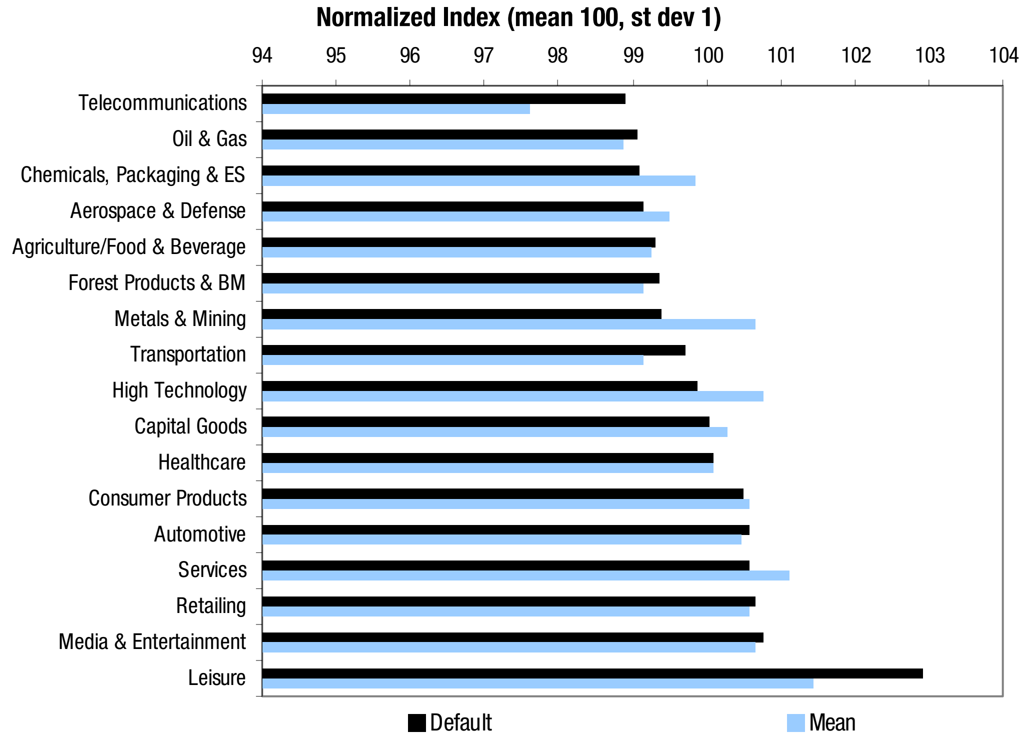
Source: Moody's database as of March 31, 2004

The implication of Exhibit 5 is that if the aggregate mean rating declines over time (and hence numerically *rises*), the future (six quarters ahead) aggregate default rate is expected to rise. The question we are posing is whether at a point in time, a higher mean rating in one industry indicates a higher future default rate for that industry.

6. Strictly speaking, we present the Hodrick-Prescott filter (λ = 1600) of the aggregate default rate as our estimate of the underlying trend. Moody's ratings are, by design, statements of credit risk through the cycle, thus it is appropriate for our purposes to remove the business-cycle fluctuations in the default rate.

Exhibit 6 presents the standardized values (mean 100, standard deviation 1) of the mean rating as of 1989q1 and the subsequent three-year default rate by industry. In fact, this metric was a useful indicator of relative credit risk. The rank order correlation is 0.78, and the correlation over values is 0.74.

Exhibit 6 **Testing the Mean Rating as a Predictor of Relative Default Risk: 1989**



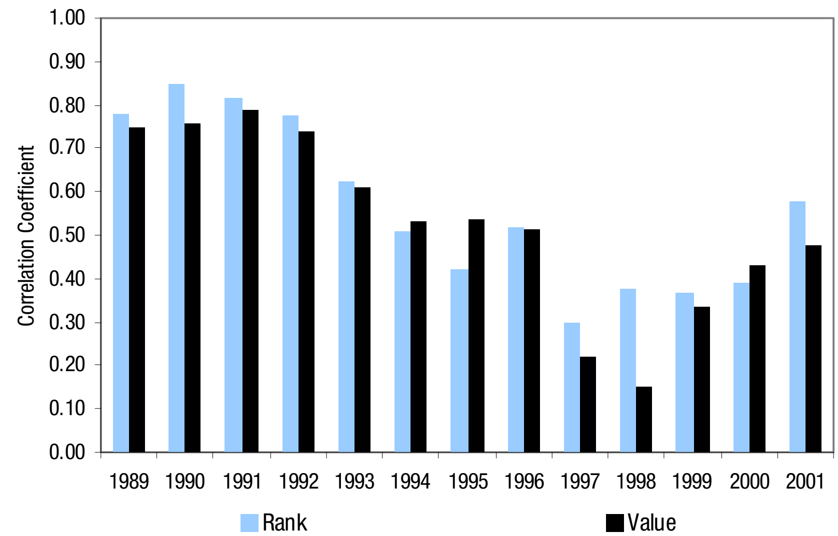
Source: Moody's database as of March 31, 2004

The Telecommunications industry had the best (numerically lowest) mean rating as of March 31, 1989, and it subsequently had the lowest cumulative default rate from April 1, 1989 through March 31, 1992. Similarly, the Leisure industry had the worst (numerically highest) mean rating, and the highest subsequent three-year default rate. The most significant rank-order error was for the Metals & Mining industry, which was ranked 14th by the mean rating, but ranked 7th by the subsequent three-year default experience.

We repeat this exercise for the first quarter of each year 1990 through 2001. The results – both the rank-order and value correlations – are presented in Exhibit 7. This metric was least effective in 1997 and 1998. That is, the values and ranks implied by the mean rating in 1997q1 were less effective in anticipating the subsequent default experience from 1997q2 through 2000q1. The effectiveness has been increasing since then. It is worth noting that on a rank-order basis, this metric has been particularly effective leading the recessions of 1991-92 and 2000-01.

Exhibit 7 **Mean Rating as a Predictor of Three-Year Relative Default Rates**

Rank-order and Value Correlations, 1989 - 2001



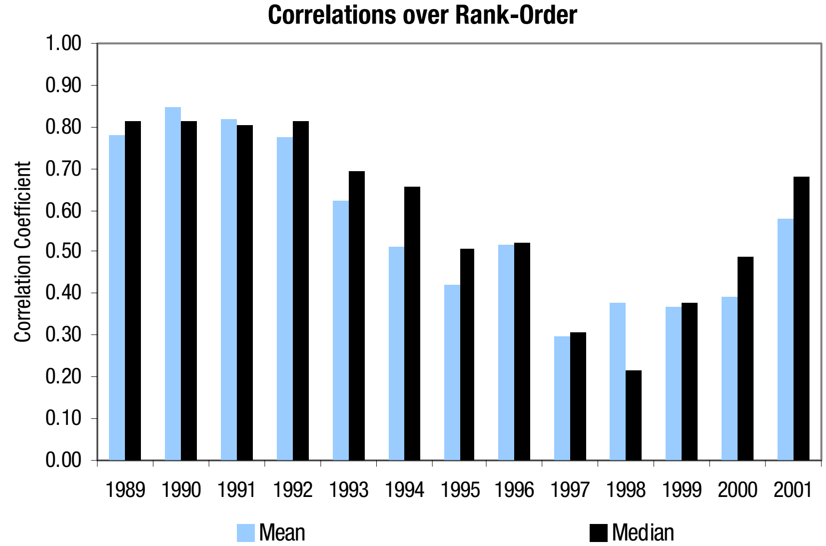
Source: Moody's database as of March 31, 2004

We can perform the same tests for other summary statistics of the ratings distribution. Consider the median rating, which is somewhat less sensitive to the assumption of a *linear* ratings scale. Exhibit 8 compares the rank-order correlations of the median rating with those of the mean rating (as reported in Exhibit 7); Exhibit 9 compares the correlations over the index values themselves.

Not surprisingly the performance of these two metrics is very similar. In anticipating the rank-order of default rates, the median rating outperforms the mean (however slightly) in ten of the thirteen years tested. However, in anticipating the relative magnitudes of default rates, it is less successful, outperforming the mean rating in seven of thirteen years.

Exhibit 8 **Comparing the Mean and Median Rating as Indicators of Relative Defaults**

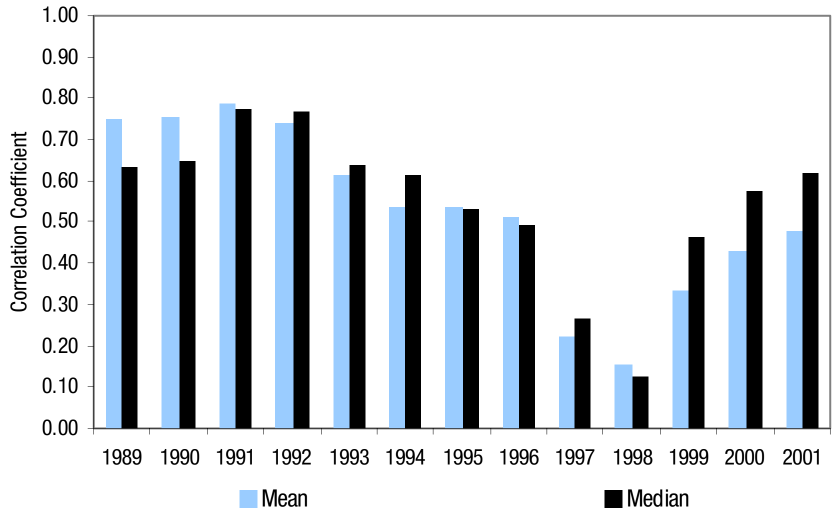
Correlations over Rank-Order



Source: Moody's database as of March 31, 2004

Exhibit 9 **Comparing the Mean and Median Rating as Indicators of Relative Defaults**

Correlation over Index Values



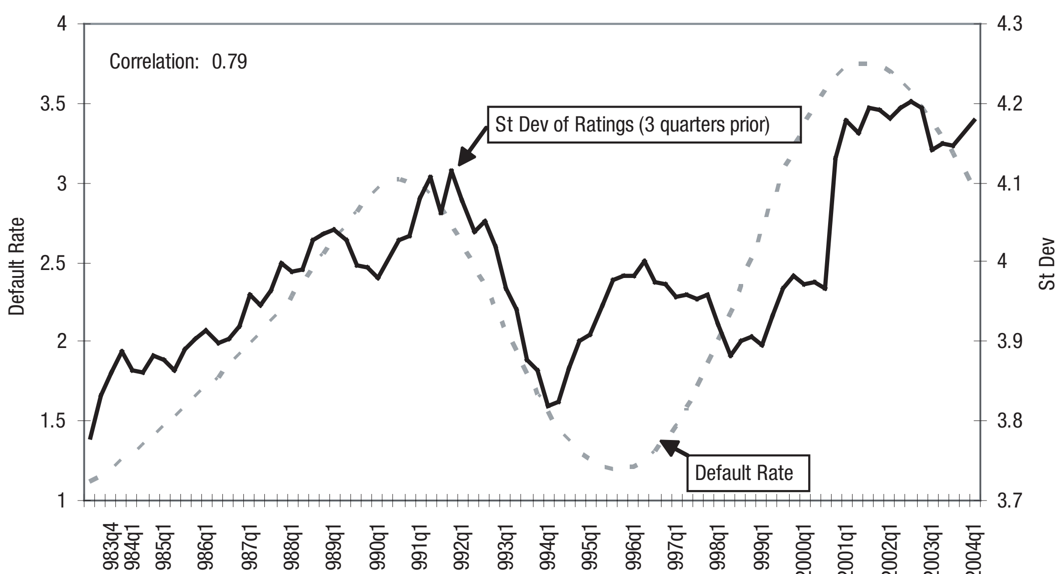
Source: Moody's database as of March 31, 2004

It has been well established that the large majority of defaults occur with spec-grade rated issuers. If industry A has an issuer rated Baa2 and another issuer rated B2, while industry B has two issuers rated Ba2, the mean (and median) rating will not distinguish between these two industries, but it is reasonable to think that A is more susceptible to default than is B. We next consider summary metrics which would distinguish this hypothetical A from B.

The first is simply the standard deviation of ratings. Greater dispersion suggests more issuers rated in the tails of the distribution, including the lower end where most defaults will be found. Indeed, Exhibit 11 indicates that this has been a particularly effective indicator in the aggregate, at very short horizons. As the dispersion of ratings (without conditioning for industrial classification) increases, the default rate tends to increase in relatively short order.

Exhibit 11 **Aggregate Default Rate and Standard Deviation of Ratings**

3 Quarter Leading Correlation of 0.79

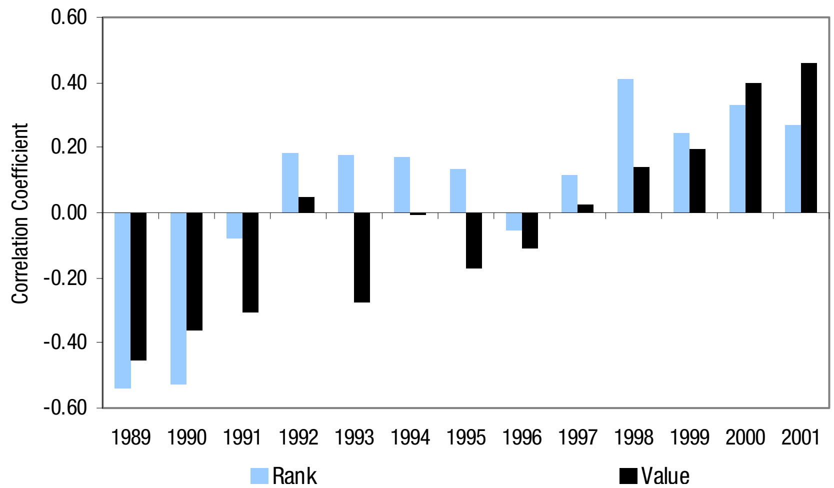


Source: Moody's database as of March 31, 2004

However, from Exhibit 12 we see that it has been nearly useless in the cross-section. In other words, it has not been helpful to compare the dispersion of ratings in one industry against that of another: the fact that industry A has a greater dispersion of ratings than does industry B does not justify any inference about the relative default risk of industry A over that of B. This is our first clear example that an indicator which is helpful for one purpose – anticipating changes in the aggregate default rate over time – may not be helpful for another purpose – anticipating relative default rates across industries.

Exhibit 12 **Standard Deviation of Ratings as a Predictor of Three-Year Relative Default Rates**

Rank-order and Value Correlations, 1989 - 2001



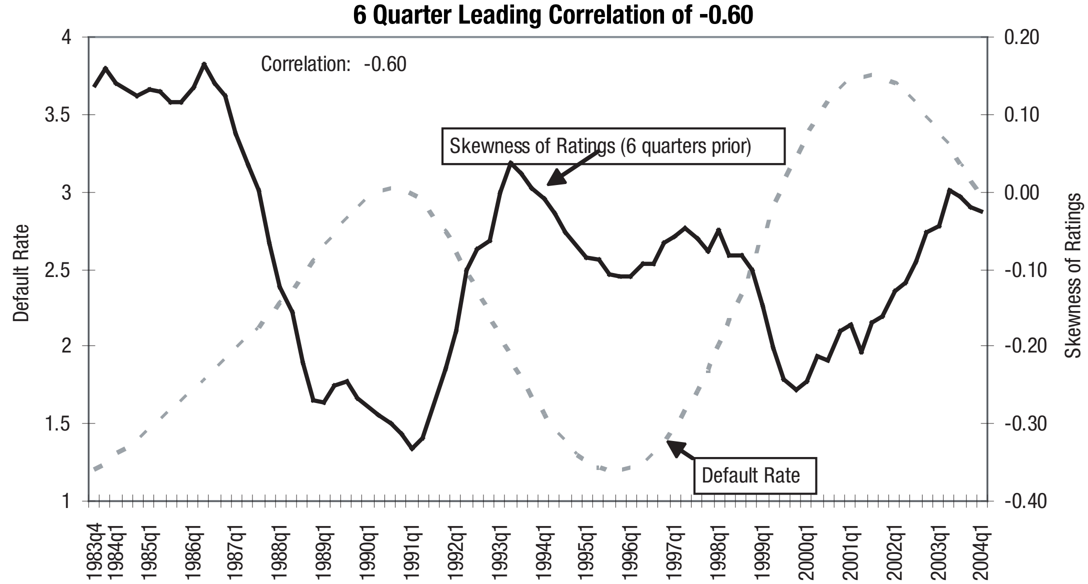
Source: Moody's database as of March 31, 2004

Of course, the standard deviation is symmetric in its treatment of very high rated and very low rated issuers. The skewness coefficient is not, and considering the fixed discrete support of the ratings scale, this summary statistic is a particularly meaningful measure of the ratings distribution.

Exhibit 13 indicates the skewness coefficient has been slightly less effective in the aggregate over time than have the other indicators considered so far.[7] However, Exhibit 14 indicates that it has been more effective in the cross-section. In predicting the rank-order of subsequent default rates, the skewness metric outperforms the mean rating in six of thirteen years; predicting the relative magnitudes of default rates, it outperforms the mean rating in seven of thirteen years.

Exhibit 13 **Aggregate Default Rate and the Skewness of Ratings**

6 Quarter Leading Correlation of -0.60

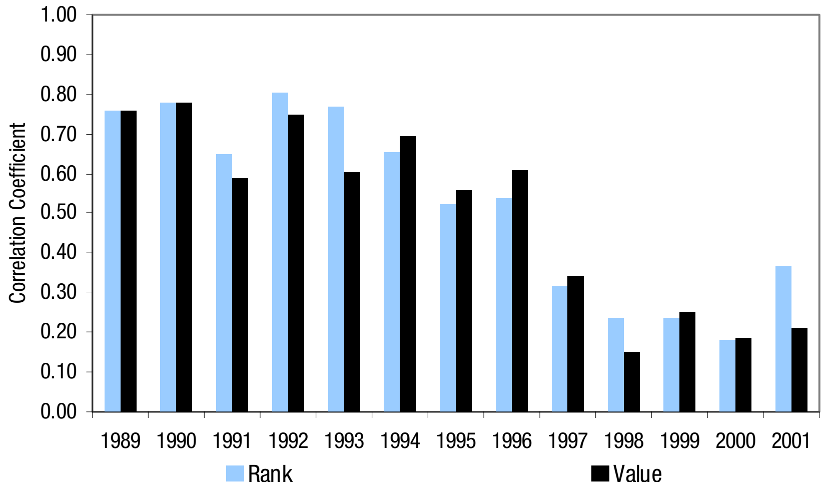


Source: Moody's database as of March 31, 2004

7. *The negative correlation is to be expected for the skewness coefficient.*

Exhibit 14 **Skewness of Ratings as a Predictor of Three-Year Relative Default Rates**

Rank-order and Value Correlations, 1989 - 2001

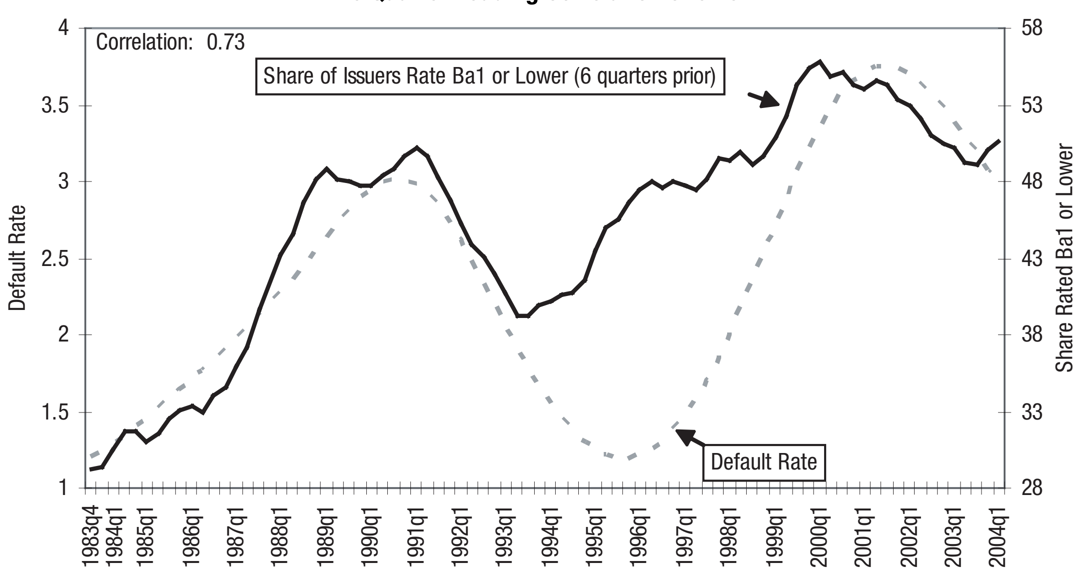


Source: Moody's database as of March 31, 2004

To isolate the lower end of the scale directly, we consider the share of issuers with spec-grade ratings. Perhaps surprisingly, this has been only marginally more effective in the aggregate than has the simple mean rating, as evidenced in Exhibit 15.

Exhibit 15 **Aggregate Default Rate and the Spec-Grade Share of Issuers**

6 Quarter Leading Correlation of 0.73



Source: Moody's database as of March 31, 2004

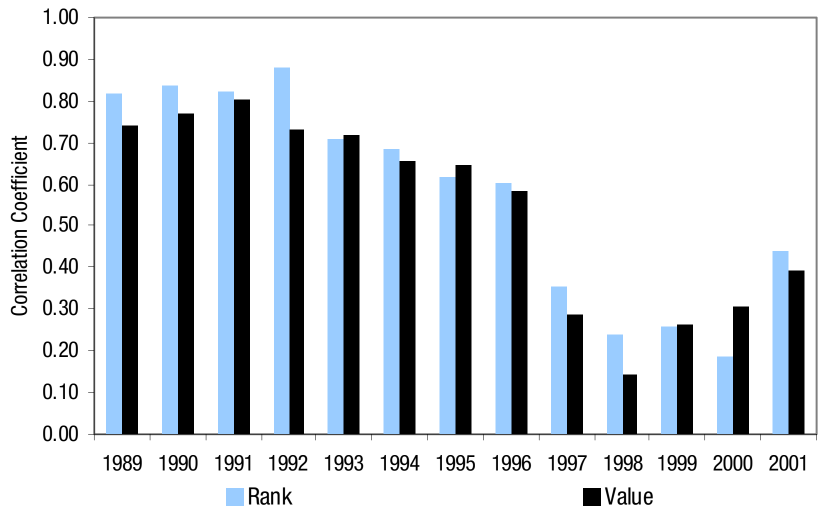
Exhibit 16 indicates that this metric has done well in anticipating relative default rates in the cross-section. On a rank-order basis, it outperforms the mean rating in eight of thirteen years and the skewness metric in twelve of thirteen years. On a value basis, its predictions are more accurate than the mean rating in seven years, and more accurate than the skewness metric in six years.

There are several other ratings-based metrics that one might consider. Perhaps ratings actions (upgrades and downgrades) anticipate relative default rates. As it turns out, while some metrics of rating actions are effective (over short time horizons) in the aggregate, they are ineffective in the cross-section.[8] Exhibits 17 and 18 detail their comparatively poor predictive power.

Ultimately, we wish to relax the assumption of a *linear* ratings scale (that is, that moving from Aaa to Aa1 represents the same change in default risk as moving from B3 to Caa1), which underlies virtually every one of these ratings-based measures. Instead, we will weight issuers in a rating category by that category's associated idealized default rate.

Exhibit 16 **Spec-Rated Share as a Predictor of Three-Year Relative Default Rates**

Rank-order and Value Correlations, 1989 - 2001



Source: Moody's database as of March 31, 2004

Exhibit 17 **Comparing the Predictive Power of Ratings-Based Metrics**

Correlations over Rank-Orders

	Downgrade Rate	Upgrade Rate	Net Rating Drift	Rating Volatility
1989	0.24	0.10	0.09	-0.21
1990	-0.19	0.25	0.03	-0.12
1991	0.26	0.04	0.19	0.29
1992	-0.19	0.08	-0.30	-0.23
1993	-0.02	-0.17	-0.11	0.05
1994	0.09	0.08	0.36	-0.02
1995	0.53	-0.20	0.33	0.45
1996	0.44	-0.18	0.34	0.57
1997	0.42	0.15	0.14	0.23
1998	0.02	0.26	0.14	-0.02
1999	0.55	0.29	0.47	0.36
2000	0.40	0.09	0.26	0.70
2001	0.47	0.62	0.61	0.19
	0.23	*0.11*	*0.20*	*0.17*

Source: Moody's database as of March 31, 2004

8. *Since changes in ratings are not significant indicators of relative credit risk across industries, it is unlikely that watchlist and outlook conditions – which anticipate changes in ratings – would be effective indicators by themselves. However, due to limitations of data, we are unable to test them in the manner described above.*

Exhibit 18

Comparing the Predictive Power of Ratings-Based Metrics

Correlations over Index Values

	Downgrade Rate	Upgrade Rate	Net Rating Drift	Rating Volatility
1989	0.20	0.12	0.06	-0.21
1990	-0.34	0.32	-0.07	-0.29
1991	0.20	0.18	0.23	0.08
1992	-0.34	0.24	-0.20	-0.39
1993	-0.03	-0.20	-0.05	0.08
1994	0.07	0.16	0.32	-0.06
1995	0.51	-0.04	0.32	0.35
1996	0.63	-0.08	0.51	0.72
1997	0.33	-0.03	0.06	0.26
1998	0.22	0.24	0.35	0.14
1999	0.53	0.30	0.33	0.33
2000	0.21	-0.35	-0.09	0.67
2001	0.43	0.59	0.56	0.28
	0.20	*0.11*	*0.18*	*0.15*

Source: Moody's database as of March 31, 2004

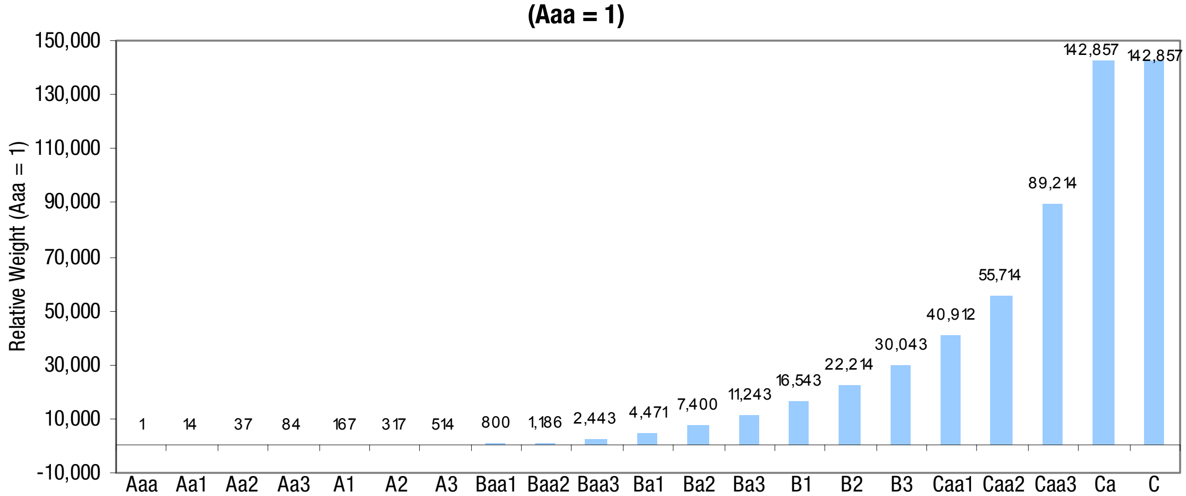
V. Ratings-Implied Expected Default Rate

From historical data we know the average loss rate associated with each rating category at multiple horizons, including the three-year horizon. Assuming a fixed recovery rate, we therefore know the corresponding default rate. We present the three-year idealized default rates in Exhibit 19, normalizing the rate for Aaa = 1. As can be readily seen, this scale is far from linear: the idealized default rate of an Aa1 rating is essentially indistinguishable from that of either the Aaa or the Aa2, whereas that of the B2 rating is very different from that of the B1 or the B3. What we see is that the distribution of ratings in the low end of the ratings scale is far more significant for default risk than is the distribution in the high end of the scale.

Exhibit 19

Three-Year Idealized Default Rates by Rating Category

(Aaa = 1)



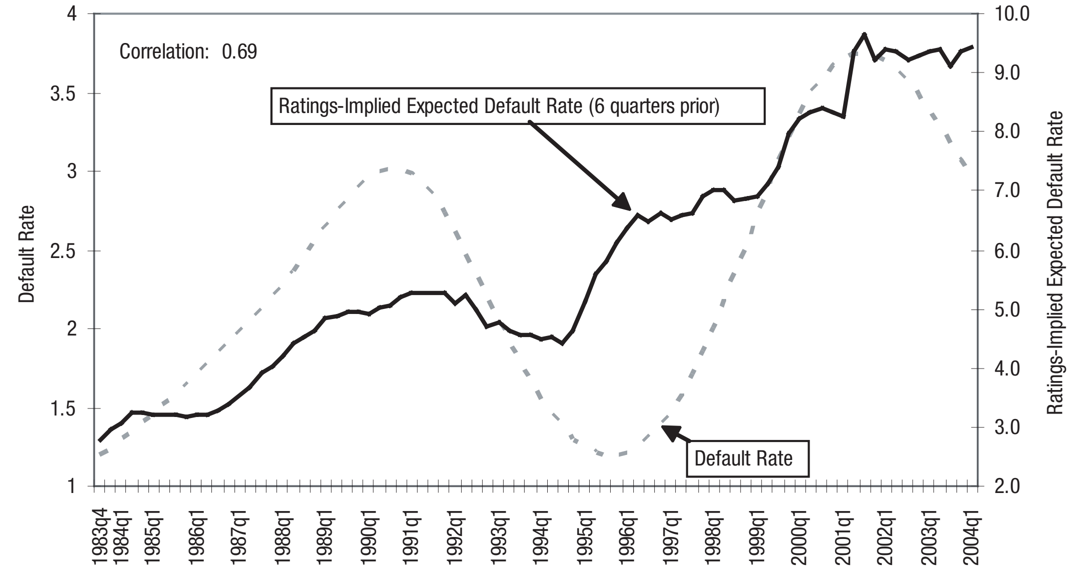
Source: Moody's

When we weight each issuer in a rating category by that category's three-year idealized default rate, the result is a ratings-implied expected default rate. However, as a first step we adjust an issuer's rating by its outlook or watchlist designation. Previous research has shown that the optimal adjustment for the purposes of anticipating default rates is to lower the rating one notch for a negative outlook, two notches for issuers on watchlist for a downgrade, increase the rating one notch for a positive outlook, and two notches for an issuer on watchlist for an upgrade. This *adjusted ratings-implied expected default rate* (EDR) is, presumably, the most meaningful summary statistic that we can draw from the ratings distribution for our purposes.

Exhibit 20 indicates, perhaps surprisingly, that in the aggregate over time it has really not been more effective than some of the other statistics we have considered thus far. But when we compare its performance in the cross-section with our other candidate indicators, we see that it is easily the dominant measure. Exhibit 21 compares the EDR metric with the simple mean rating as an indicator of the rank-order of relative industry default rates. In nine out of thirteen years it outperforms the mean, sometimes substantially so.

Exhibit 20 **Aggregate Default Rate and the Ratings-Implied Expected Default Rate**

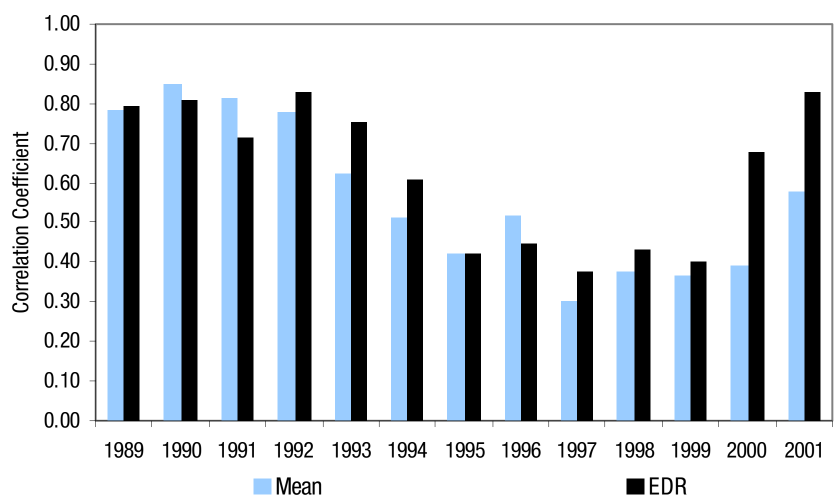
6 Quarter Leading Correlation of 0.69



Source: Moody's database as of March 31, 2004

Exhibit 21 **Comparing the Mean and the Ratings-Implied EDR as Indicators of Relative Defaults**

Correlations over Rank-Order

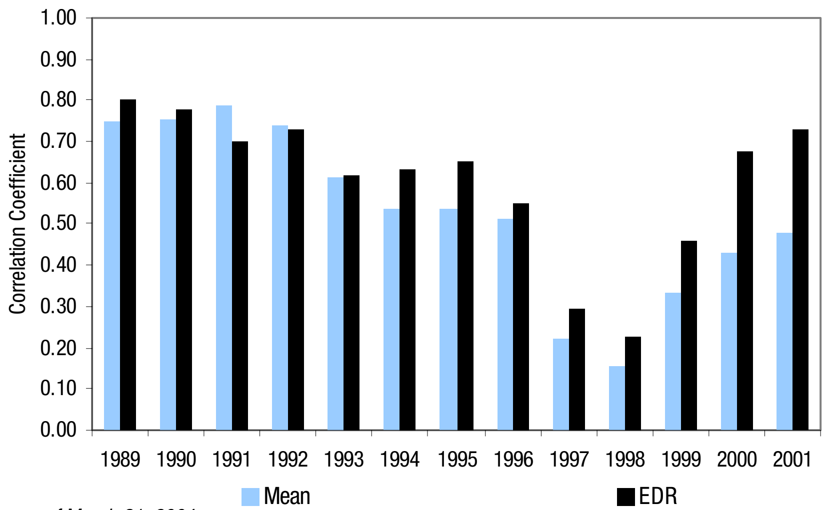


Source: Moody's database as of March 31, 2004

Exhibit 22 compares the two candidate indicators as predictors of the relative magnitudes of industry default rates. Here the superiority of the EDR is more evident: it outperforms the simple mean in eleven of thirteen years, and again, the difference is often substantial.

Exhibit 22 **Comparing the Mean and Ratings-Implied EDR as Indicators of Relative Defaults**

Correlations over Index Values



Source: Moody's database as of March 31, 2004

Finally, Exhibits 23 and 24 compare the indicators we have presented above, first in their ability to rank-order relative default rates, and second in their ability to gauge the magnitude of relative default rates. In each table, the best performing metric in each year is highlighted. The simple average correlation is reported in the last line of each table.

Exhibit 23 **Comparing the Predictive Power of Ratings-Based Metrics**

Correlations over Rank-Orders

	EDR	Mean	Median	St Dev	Skewness	Spec-Grade Share
1989	0.79	0.78	0.81	-0.54	0.76	**0.82**
1990	0.81	**0.85**	0.81	-0.53	0.78	0.84
1991	0.72	0.82	0.81	-0.08	0.65	**0.82**
1992	0.83	0.78	0.81	0.18	0.81	**0.88**
1993	0.76	0.62	0.69	0.18	**0.77**	0.71
1994	0.61	0.51	0.66	0.17	0.65	**0.69**
1995	0.42	0.42	0.51	0.14	0.52	**0.62**
1996	0.45	0.52	0.52	-0.05	0.54	**0.60**
1997	**0.38**	0.30	0.31	0.12	0.32	0.36
1998	**0.43**	0.38	0.22	0.41	0.24	0.24
1999	**0.40**	0.37	0.38	0.24	0.24	0.26
2000	**0.68**	0.39	0.49	0.33	0.18	0.19
2001	**0.83**	0.58	0.68	0.27	0.37	0.44
	0.62	*0.56*	*0.59*	*0.07*	*0.52*	*0.57*

Source: Moody's database as of March 31, 2004

Exhibit 24

Comparing the Predictive Power of Ratings-Based Metrics

Correlations over Index Values

	EDR	Mean	Median	St Dev	Skewness	Spec-Grade Share
1989	**0.80**	0.75	0.63	-0.45	0.76	0.74
1990	0.78	0.76	0.65	-0.36	**0.78**	0.77
1991	0.70	0.79	**0.77**	-0.31	0.59	**0.80**
1992	0.73	0.74	**0.77**	0.05	0.75	0.73
1993	0.62	0.61	0.64	-0.28	0.60	**0.72**
1994	0.63	0.53	0.62	-0.01	**0.70**	0.65
1995	**0.65**	0.54	0.53	-0.17	0.56	0.65
1996	0.55	0.51	0.49	-0.11	**0.61**	0.58
1997	0.29	0.22	0.26	0.03	**0.34**	0.29
1998	**0.23**	0.15	0.13	0.14	0.15	0.14
1999	**0.46**	0.33	0.46	0.19	0.25	0.26
2000	**0.68**	0.43	0.57	0.40	0.19	0.31
2001	**0.73**	0.48	0.62	0.46	0.21	0.39
	0.60	*0.53*	*0.55*	*-0.03*	*0.50*	*0.54*

Source: Moody's database as of March 31, 2004

From Exhibit 23 we see that in predicting the rank-order of relative default rates, the EDR was the best performing metric five times, while the share of issuers with speculative grade ratings was best seven times. However, the EDR was still best on average: in those years when the spec-grade share outperformed the EDR, the difference was generally slight, but when the EDR outperformed the spec-grade share, the difference was dramatic. The EDR was least successful in 1997, with a rank-order correlation of only 0.38. But this compares favorably with the low points of the other indicators: the mean rating (0.30 in 1997), the median rating (0.22 in 1998), the standard deviation of ratings (-0.54 in 1989), the skewness of ratings (0.18 in 2000), and the spec-grade share (0.19 in 2000).

Exhibit 24 indicates that the EDR was the best at anticipating the relative magnitudes of the default rates six times, followed by the skewness measure which was best four times. Again, however, the EDR is clearly the best on average. Its low point, a correlation of only 0.23 in 1998, still compares favorably with the other indicators: mean rating (0.15 in 1998), median rating (0.13 in 1998), standard deviation of ratings (-0.45 in 1989), skewness of ratings (0.15 in 1998), and the spec-grade share (0.14 in 1998).

Taken together, the EDR is both the best predictor of rank-orders and the best predictor of relative magnitudes of subsequent three-year default rates. This has been particularly true since 1998. While other metrics have been "surprised" by the subsequent relative default experiences, the EDR has remained very effective.

The test of an indicator in the aggregate over time is a test of whether that indicator changes significantly in anticipation of two great default waves. The test in the cross-section is a test of whether an indicator changes subtly across industries which, frequently, are only subtly different in default risk. The aggregate mean rating (on a linear scale) and the adjusted rating-implied expected default rate (on the non-linear scale) both experience similar large changes in anticipation of the two default waves; hence they are about equally effective as aggregate indicators. But the rating-implied expected default rate is more sensitive to subtle differences in the ratings distribution across industries, differences which have been important in identifying relative risk in the cross-section. As a result, while it is not more effective in the aggregate over time, the ratings-implied EDR is more effective in the cross-section at a specific point in time.

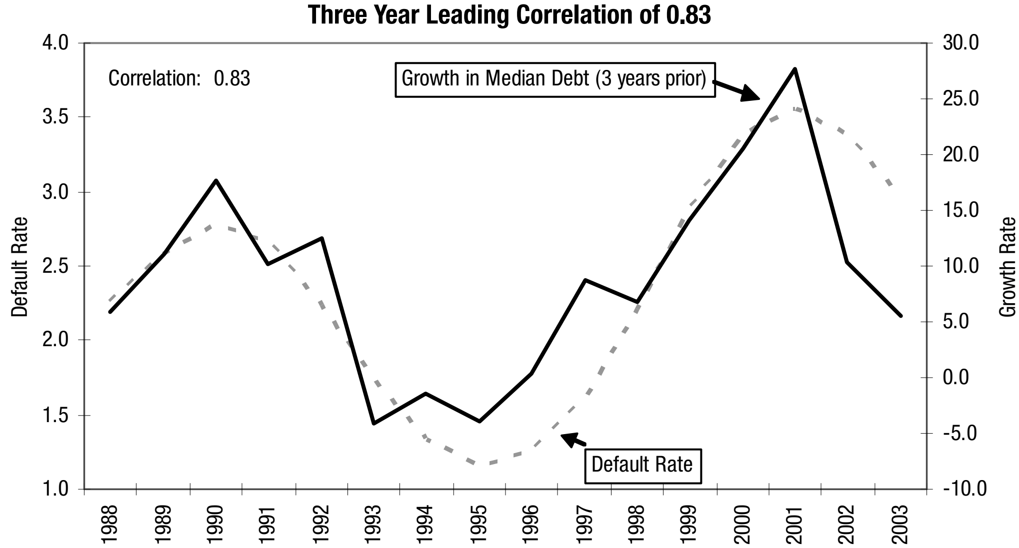
VI. Financial Ratios

It is common practice in credit analysis to use financial statement data to compare the credit worthiness of different issuers. It is not unreasonable to expect that financial data might indicate relative default risk across industries as well. In this section, we test several common measures: debt growth, asset growth, and coverage, leverage, liquidity and cash flow-to-debt ratios.[9]

Exhibits 25 – 30 show that each of these measures has been effective – and sometimes extremely effective – in anticipating changes in the aggregate default rate trend, though at different leading time horizons. Our objective is to see whether they are effective at identifying relative default risk across industries. As an example, from Exhibit 25 we can see that growth in the median level of debt in the aggregate (i.e., without regard to industrial classification) is a very powerful leading indicator of changes in the aggregate default rate. But is it the case that higher debt growth in industry A than B implies greater default risk in A?

Exhibit 25 **Aggregate Default Rate and Growth in the Median Level of Debt**

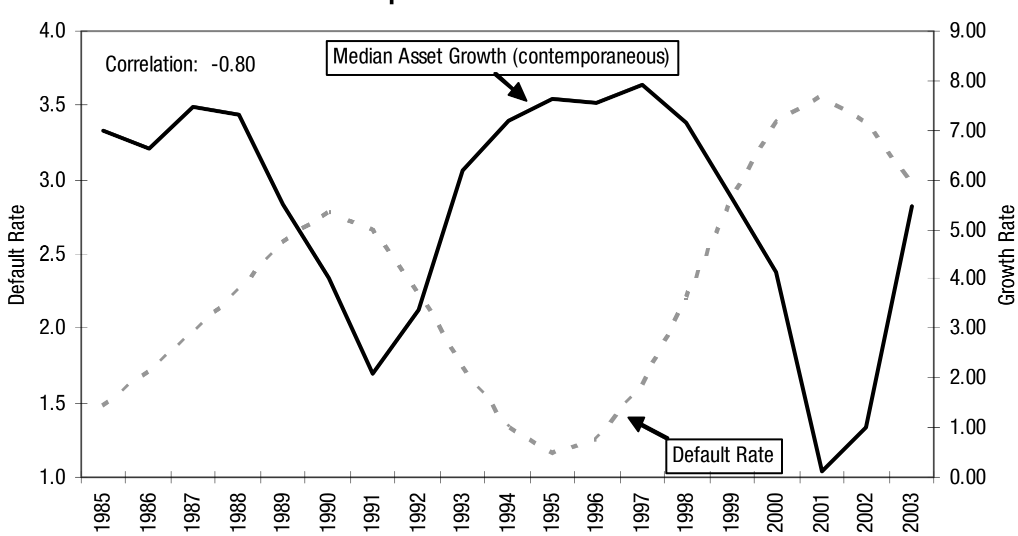
Three Year Leading Correlation of 0.83



Source: Moody's database as of March 31, 2004 and Compustat

Exhibit 26 **Aggregate Default Rate and Median Asset Growth**

Contemporaneous Correlation of -0.80



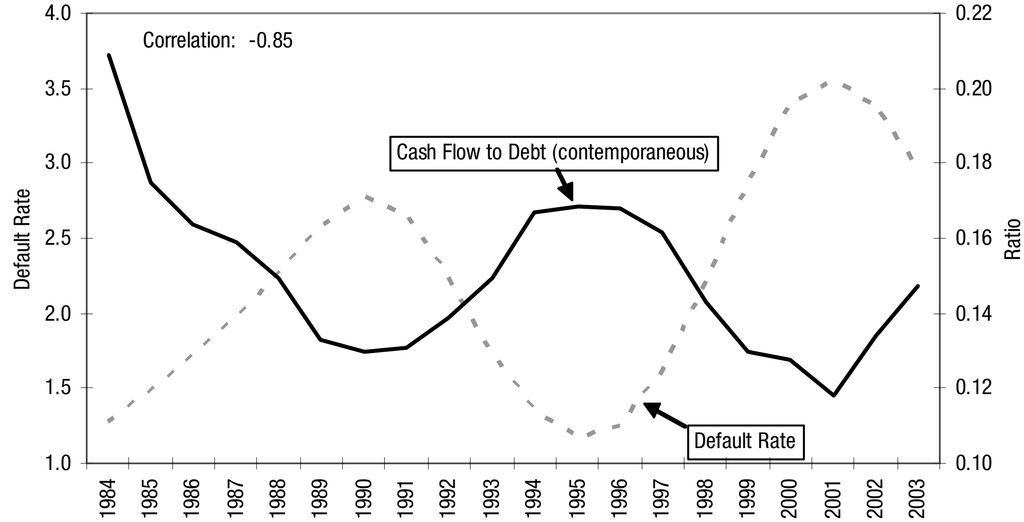
Source: Moody's database as of March 31, 2004 and Compustat

9. *Please see the Appendix for definitions.*

Exhibit 27

Aggregate Default Rate and Median Cash Flow-to-Debt Ratio

Contemporaneous Correlation of -0.85

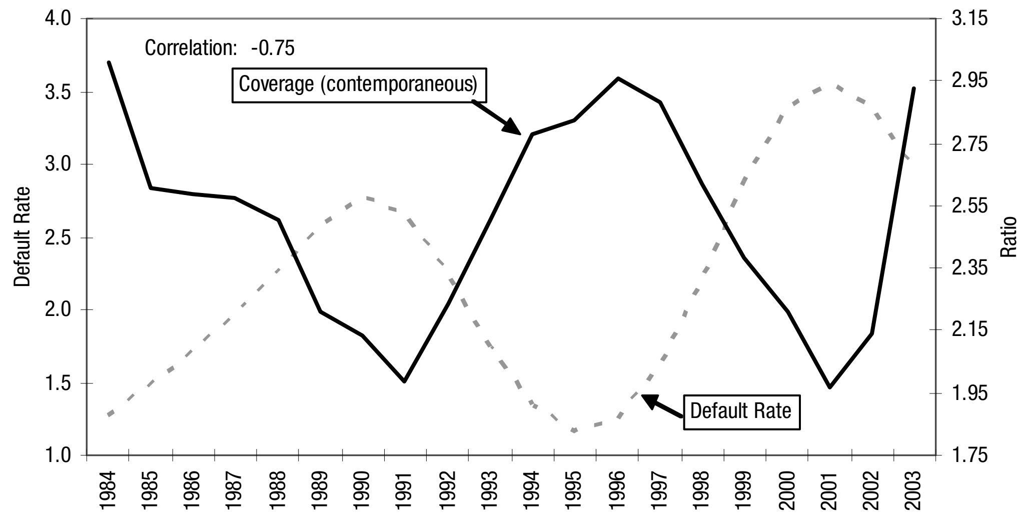


Source: Moody's database as of March 31, 2004 and Compustat

Exhibit 28

Aggregate Default Rate and Median Coverage Ratio

Contemporaneous Correlation of -0.75

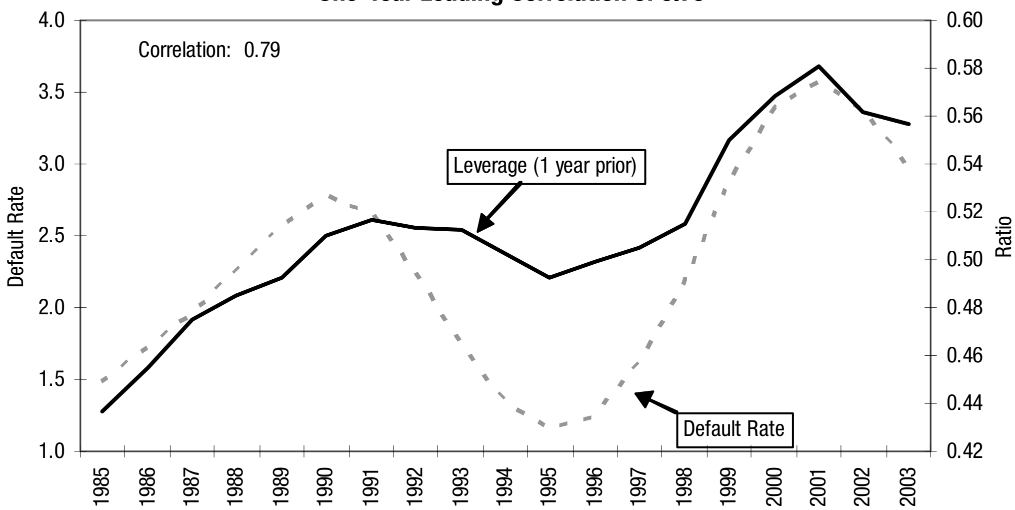


Source: Moody's database as of March 31, 2004 and Compustat

Exhibit 29

Aggregate Default Rate and Median Leverage Ratio

One-Year Leading Correlation of 0.79

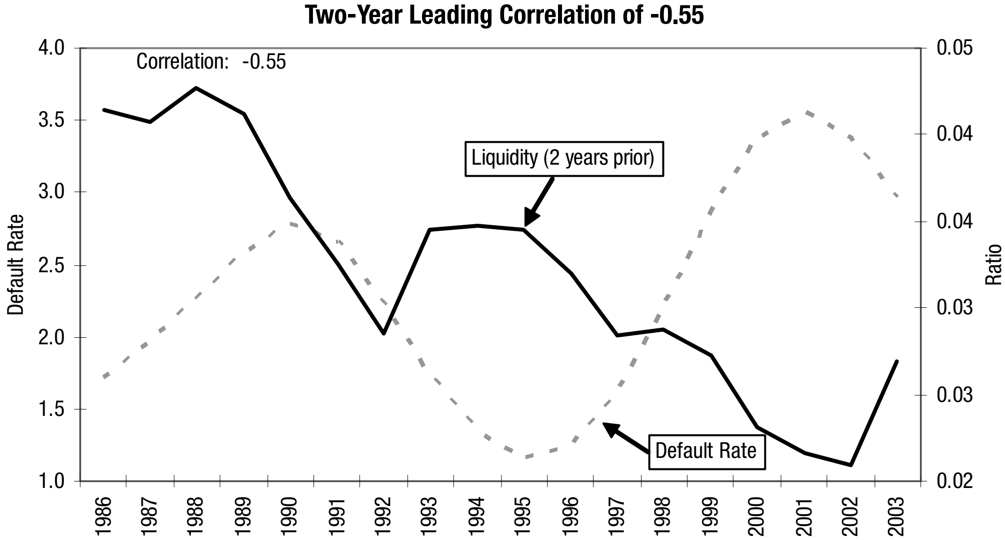


Source: Moody's database as of March 31, 2004 and Compustat

Exhibit 30

Aggregate Default Rate and Median Liquidity Ratio

Two-Year Leading Correlation of -0.55



Source: Moody's database as of March 31, 2004 and Compustat

In Exhibits 31 and 32, we present the historical performance of these financial metrics as predictors of the rank-order of relative default rates and the relative magnitude of default rates. The median leverage ratio emerges as the most effective financial indicator for both purposes. On a rank-order basis, it is the most effective indicator five times, and on a value basis, it is the most effective eight times, during these thirteen years.

Exhibit 31

Comparing the Predictive Power of Financial Statement Metrics

Correlations over Rank-Orders

	Growth in Median Debt	Median Asset Growth	Median Coverage	Median Leverage	Median Cash Flow/Debt	Median Liquidity
1989	0.50	-0.45	0.55	**0.86**	0.80	-0.03
1990	-0.45	-0.14	0.54	**0.68**	0.67	-0.25
1991	0.16	**0.64**	0.58	0.52	0.54	-0.13
1992	-0.22	0.09	0.27	**0.39**	0.14	-0.36
1993	-0.13	-0.35	-0.16	**0.60**	0.24	-0.41
1994	**0.51**	-0.45	-0.09	0.47	0.01	-0.20
1995	0.43	-0.42	0.02	**0.69**	0.50	-0.32
1996	**0.47**	-0.21	0.34	0.29	0.41	-0.41
1997	0.10	0.04	0.15	0.11	**0.16**	-0.06
1998	-0.26	**0.51**	0.31	-0.07	0.11	0.21
1999	-0.28	**0.38**	-0.06	-0.18	-0.15	0.09
2000	0.28	0.21	**0.37**	0.12	0.27	0.13
2001	0.23	0.36	0.56	0.47	**0.76**	-0.19
	0.10	*0.02*	*0.26*	***0.38***	*0.34*	*-0.15*

Source: Moody's database as of March 31, 2004 and Compustat

Exhibit 32

Comparing the Predictive Power of Financial Statement Metrics

Correlations over Index Values

	Growth in Median Debt	Median Asset Growth	Median Coverage	Median Leverage	Median Cash Flow/Debt	Median Liquidity
1989	0.72	-0.41	0.54	**0.78**	0.59	-0.14
1990	-0.48	-0.16	0.50	**0.64**	0.54	-0.25
1991	0.25	**0.67**	0.53	0.55	0.51	-0.03
1992	-0.24	0.00	0.34	**0.46**	0.29	-0.34
1993	-0.29	-0.37	0.03	**0.62**	0.33	-0.29
1994	0.35	-0.53	-0.04	**0.56**	0.13	-0.27
1995	0.15	-0.23	0.18	**0.71**	0.53	-0.23
1996	0.16	-0.10	0.32	**0.49**	0.40	-0.27
1997	0.10	-0.07	0.10	**0.17**	0.12	-0.15
1998	-0.22	**0.44**	0.31	-0.04	0.20	0.27
1999	-0.35	**0.34**	-0.01	-0.14	-0.01	0.19
2000	0.06	-0.30	**0.49**	0.14	0.45	-0.08
2001	0.38	-0.21	0.68	0.31	**0.72**	-0.05
	0.05	*-0.07*	*0.31*	***0.40***	*0.37*	*-0.13*

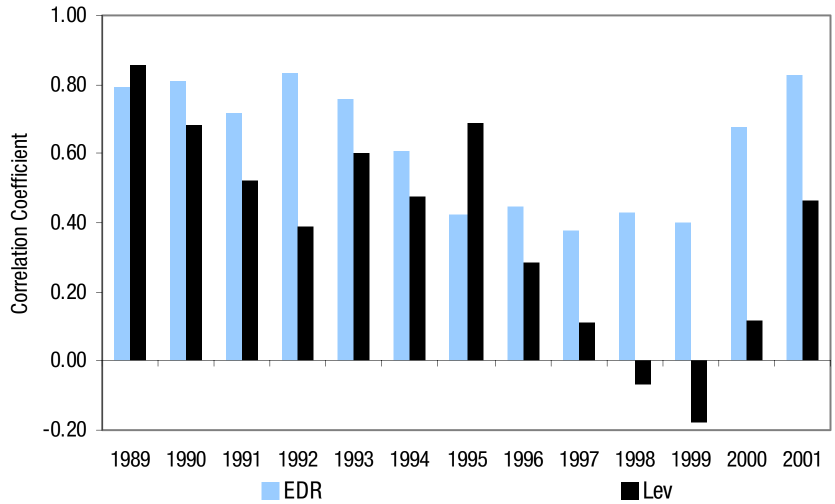
Source: Moody's database as of March 31, 2004 and Compustat

However, comparing these results with the results of the ratings-based metrics presented in Exhibits 23 and 24, the financial statement metrics are clearly less effective. The average rank-order correlation for the median leverage ratio is 0.38, but for the adjusted ratings-implied expected default rate it is 0.62. On a value-basis, the average correlation of the leverage ratio is 0.40, and that of the adjusted ratings-implied EDR is 0.60.

Exhibits 33 and 34 compare the adjusted ratings-implied EDR, which is the most effective ratings-based indicator, with the median leverage ratio, which is the most effective financial statement-based indicator. In anticipating the rank-order of relative defaults, the ratings-implied EDR outperforms the leverage ratio in eleven of thirteen years, and often quite substantially. To anticipate the relative magnitude of default rates, it outperforms the leverage ratio in twelve of thirteen years.

Exhibit 33 **Comparing the Ratings-Implied EDR and Median Leverage Ratio as Indicators of Relative Default**

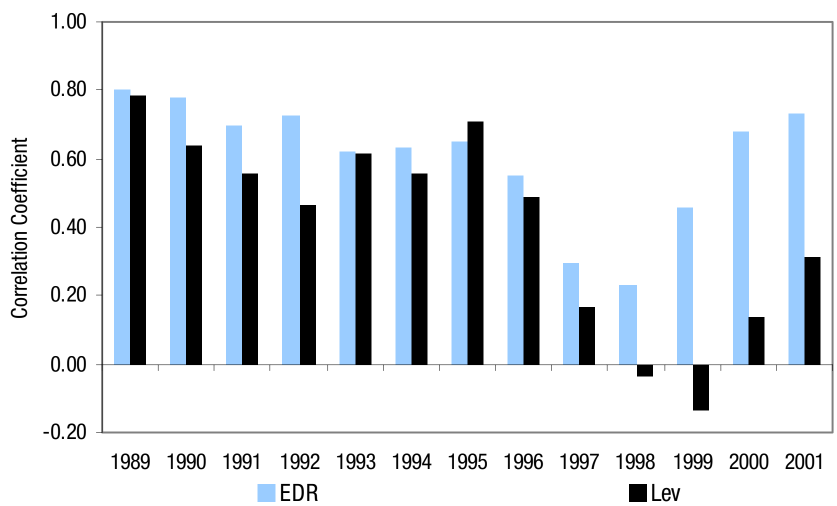
Correlations over Rank-Order



Source: Moody's database as of March 31, 2004 and Compustat

Exhibit 34 **Comparing the Ratings-Implied EDR and Median Leverage Ratio as Indicators of Relative Default**

Correlations over Index Values



Source: Moody's database as of March 31, 2004 and Compustat

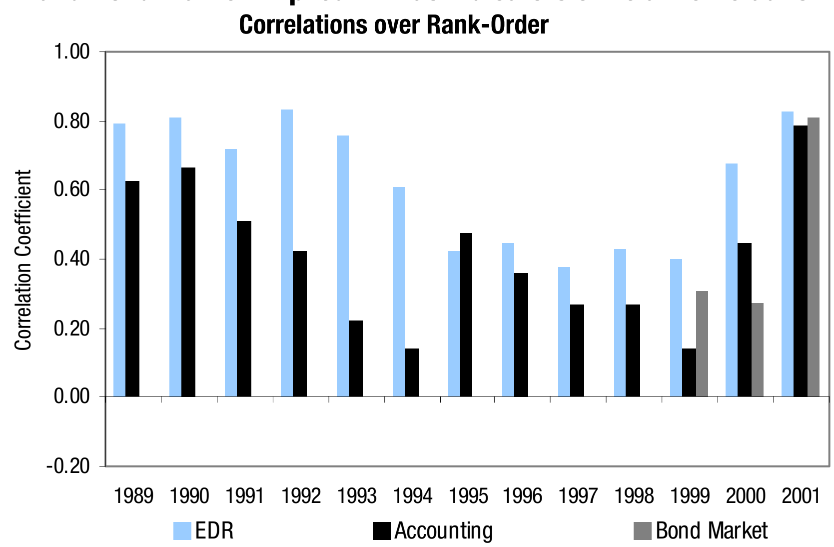
VII. Market-Implied and Financial Statement-Implied Models

In this section we evaluate two rating models as indicators of relative three-year default risk across industries. The first uses bond market data and option-adjusted spreads to impute a credit rating to an issuer. The second is an optimal combination of financial statement data, such as those presented in Section VI., translated into an implied credit rating. For both models, we will take the implied rating distributions and weight them by the three-year idealized default rates.[10] The result, on the one hand, is a *bond market rating-implied expected default rate* (henceforth *bond-implied EDR*), and on the other is a *financial statement rating-implied expected default rate* (*financial statement-implied EDR*).

10. *In neither case is there the equivalent of an outlook or watchlist assignment, hence we do not make this first-step adjustment.*

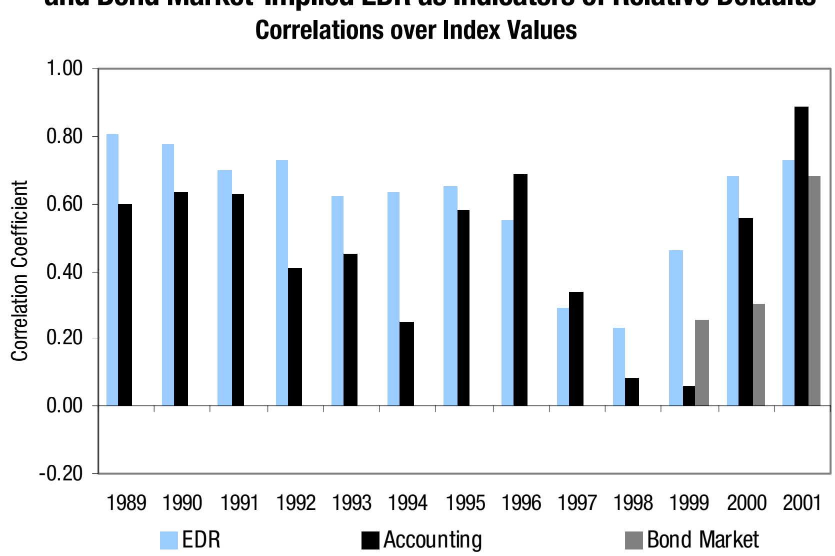
Exhibit 35 compares the Moody's adjusted rating-implied EDR, as presented in Section V., with the financial statement-implied EDR and with the bond-implied EDR. Due to limited data, we are only able to test the bond-implied EDR for the years 1999, 2000 and 2001. The comparison is made over the rank-order correlations with the subsequent default rates. Exhibit 36 compares these metrics on a value-correlation basis.

Exhibit 35 **Comparing the Moody's Rating-Implied EDR, Financial Statement-Implied EDR, and Bond Market-Implied EDR as Indicators of Relative Defaults**



Source: Moody's database as of March 31, 2004 and Compustat

Exhibit 36 **Comparing the Moody's Rating-Implied EDR, Financial Statement-Implied EDR, and Bond Market-Implied EDR as Indicators of Relative Defaults**



Source: Moody's database as of March 31, 2004 and Compustat

The financial statement-implied EDR provides a better rank-ordering of default rates than does the Moody's ratings-implied EDR only once, in 1995, and the difference for that year is slight. In the three years of testable data, the bond market-implied EDR has never outperformed the Moody's ratings-implied EDR in anticipating the rank-order of default rates. On average, the Moody's EDR has been the most effective, with an average rank-order correlation of 0.62 compared with 0.41 for the financial statement EDR. From 1999 through 2001, the Moody's EDR averaged 0.64 against 0.46 for both the financial statement- and bond market-implied EDR's.

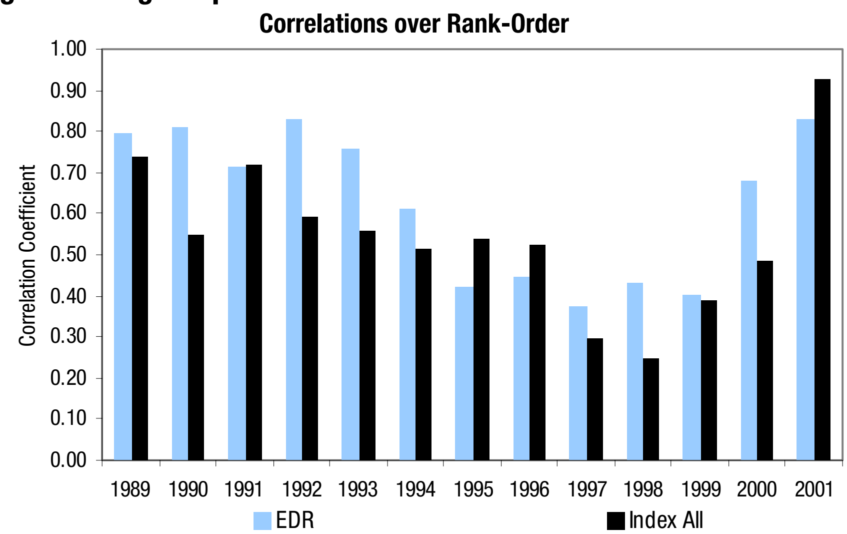
As indicators of the relative magnitude of default rates, the financial statement-implied EDR outperformed the Moody's EDR three times, in 1996, 1997 and 2001. Again, the bond market-implied EDR, thus far, has not outperformed the Moody's EDR. Over the full sample, the Moody's EDR average correlation is 0.60, compared with 0.47 for the financial statement-implied EDR. For the sub-sample 1999 through 2001, its average of 0.62 compares very favorably with that of the financial statement-implied EDR (0.50) and the bond market-implied EDR (0.41).

VIII. Composite Index

Historically, the Moody's ratings-implied expected default rate, when first adjusted for outlook and watchlist designations, has been the single most effective leading indicator of relative industry three-year default rates among all examined. But the fact that no other indicator is, by itself, more effective does not mean that some combination of indicators might not be. In this section, we test two naïve, equally-weighted indexes, and also find an "optimal" index, fit in-sample to the historical data.

Our first candidate index is constructed as the simple average of the normalized values of every indicator we have considered above, plus metrics drawn from recent rating actions. Exhibit 37 compares the performance of this index against the Moody's EDR benchmark on a rank-order basis; Exhibit 38 compares them on a value basis.

Exhibit 37 **Comparing the Ratings-Implied EDR and a Naïve Index as Indicators of Relative Default**

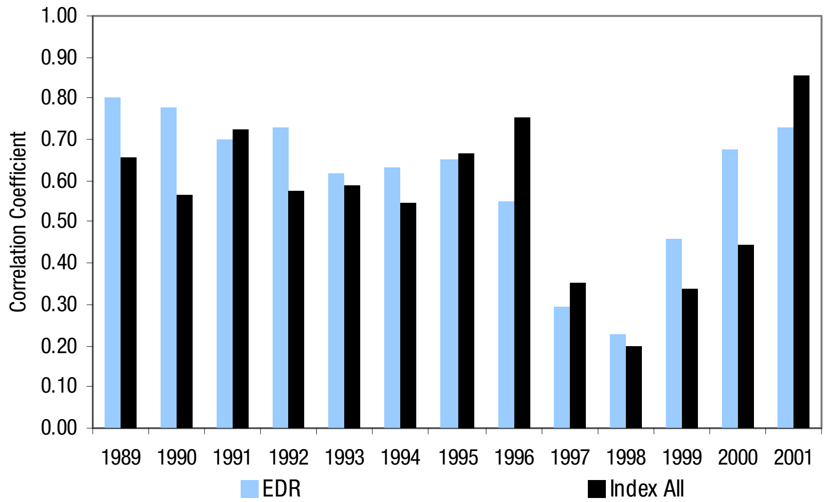


Source: Moody's database as of March 31, 2004 and Compustat

This naïve index does not offer real improvement over the Moody's adjusted ratings-implied expected default rate, outperforming the latter in only four years, however slightly. The index does a better job anticipating the relative values of default rates in only five of the thirteen years tested.

Exhibit 38 **Comparing the Ratings-Implied EDR and a Naïve Index as Indicators of Relative Default**

Correlations over Index Values



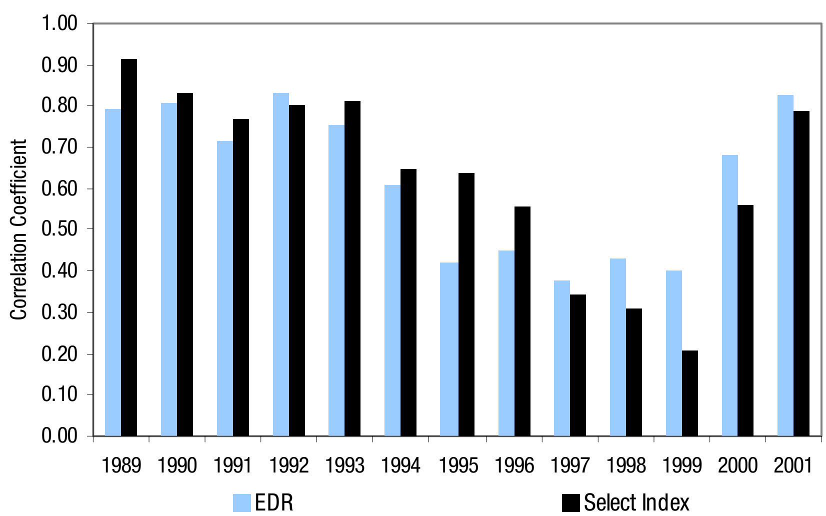
Source: Moody's database as of March 31, 2004 and Compustat

Of course, many of the metrics incorporated in this first candidate composite index are, individually, unhelpful – even counter-productive – in anticipating relative three-year default rates. The second index we test is formed (again with equal weights) over only those metrics which have an average correlation of at least 0.40 with the subsequent relative default values. Exhibit 39 compares this "selected index" with the EDR benchmark on a rank-order basis, while Exhibit 40 compares them on a value basis.

This index is comparable to the EDR benchmark, though it does not clearly dominate it. From Exhibit 39 we see that it outperformed the EDR on a rank-order basis seven times, sometimes substantially so. Its average correlation is essentially identical (0.63 for the index, 0.62 for the Moody's EDR). Exhibit 40, on the other hand, does suggest that this composite index is more effective than the EDR alone at anticipating relative default values, outperforming the latter in nine of thirteen years. Its average correlation is 0.62, while for the Moody's benchmark it is 0.60. The difference is slight, but recall that while the components of this index were deliberately selected, the combination of them is completely naïve – equal weights applied to all.

Exhibit 39 **Comparing the Ratings-Implied EDR and a Selected Index as Indicators of Relative Default**

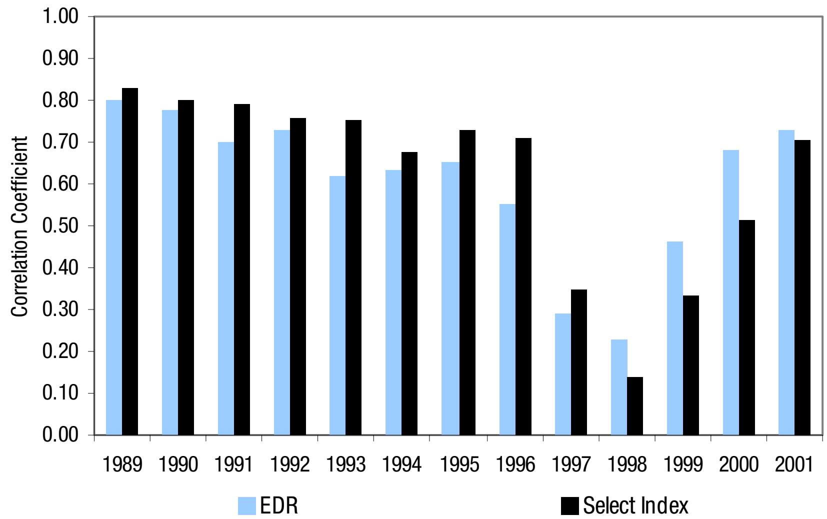
Correlations over Rank-Order



Source: Moody's database as of March 31, 2004 and Compustat

Exhibit 40 **Comparing the Ratings-Implied EDR and a Selected Index as Indicators of Relative Default**

Correlations over Index Values



Source: Moody's database as of March 31, 2004 and Compustat

Finally, to suggest the potential benefits of incorporating information beyond the Moody's ratings, we find "optimal" weights to attach to the components of this index. In particular, we define several sub-indexes, which are formed by equally weighting their constituent metrics: first, the Moody's adjusted ratings-implied expected default rate by itself; second, an index formed over other Moody's ratings metrics which are individually effective in anticipating default rates; third, an index formed over the most useful financial statement data and the financial statement-implied expected default rates; fourth, an index formed over the bond-market implied ratings; and fifth, our first candidate index – the naïve composite formed over every metric.

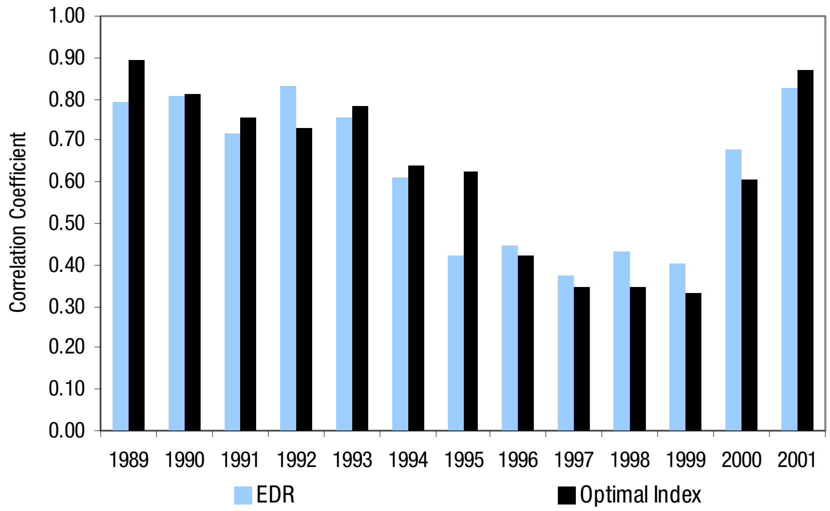
These sub-indexes are then fit to the sample default data. The result, of course, may be of no use out of sample. This is intended primarily to demonstrate some of the gains that *might* be had from incorporating such information; it is not intended to demonstrate a method for obtaining those gains. We are interested in knowing if the in-sample fit is only marginally better than the Moody's benchmark index alone or if it is significantly better, in which case a properly specified empirical model might be worth pursuing.

The best fit is found by putting 29% weight on the Moody's benchmark index, another 16% on additional Moody's metrics, 23% on the financial statement composite, and 32% on the naïve composite formed over all the metrics.

The results are presented in Exhibits 41 and 42. Exhibit 41 indicates that this optimal composite index does a better job at anticipating the rank-order of subsequent three-year default rates seven times (however slightly). On average, it is essentially equally effective, with an average rank-order correlation of 0.63 compared with 0.62 for the Moody's adjusted ratings-implied EDR.

Exhibit 41 **Comparing the Ratings-Implied EDR and an Optimal Index as Indicators of Relative Default**

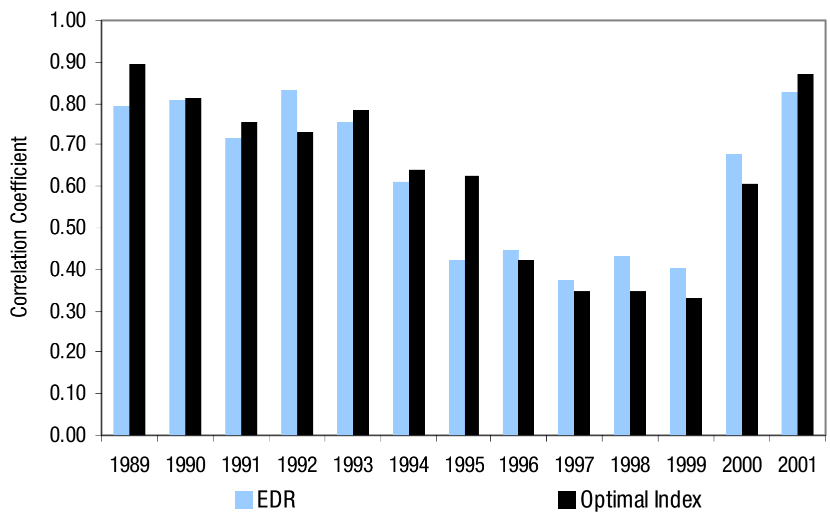
Correlations over Rank-Order



Source: Moody's database as of March 31, 2004 and Compustat

Exhibit 42 **Comparing the Ratings-Implied EDR and an Optimal Index as Indicators of Relative Default**

Correlations over Index Values



Source: Moody's database as of March 31, 2004 and Compustat

From Exhibit 42 we see that as an indicator of relative magnitudes of default rates, this optimal composite index (which, of course, we reiterate is an in-sample fit to the value data) is much more effective, dominating the Moody's benchmark index in ten of thirteen years. On average, it has a correlation of 0.64 compared with 0.60 for the Moody's indicator.

IX. Conclusion

The analysis in this Special Comment is intended to answer several basic questions about industrial default risk. First, how should investors use Moody's issuer ratings to form a judgment of the relative default risk of different industries? Second, historically, how helpful has that measure been at correctly discerning relative risk? Third, how does the effectiveness of this purely ratings-based metric compare with the effectiveness of commonly accepted key financial ratios and some empirical rating models? And fourth, is there room for improvement by incorporating additional information beyond the ratings alone?

After exploring a variety of plausible summary statistics, we find that one measure clearly dominates all others: the adjusted ratings-implied expected default rate. It is interesting to note that as an indicator of changes in the aggregate default rate, the measure is not more effective than some other ratings-based metrics, but is more effective in discerning relative risk in the cross-section.

The value of this Moody's ratings-based metric becomes more apparent when we compare it with some standard, commonly-accepted financial ratios, which, in some cases, offer no explanatory power of relative risk (though, again, in all cases they offer substantial explanatory power of inter-temporal aggregate risk). Only the coverage, leverage and cash flow-to-debt ratios emerge as having any predictive power in the cross-section.

We also compare this Moody's benchmark indicator with two ratings models, one based on bond yields, and the other based on financial statement data. The evidence suggests that neither is as effective as the Moody's indicator for our purposes.

Finally, we test the predictive power of different composite indexes formed over various metrics. A naïve composite, formed as an equally-weighted average taken over every metric, was approximately as effective as the Moody's benchmark. However, a second index, formed as an equally-weighted average taken over only those metrics that were individually effective indicators, was more effective than the Moody's benchmark. The last index we tested was formed by finding weights to best fit the sample data, and it was clearly more effective than the Moody's index. This implies that there should be gains to a well-specified empirical model that combines ratings data with financial statement and market data to better anticipate relative default rates.

X. Appendix

Downgrade (Upgrade)

An issuer is considered downgraded (upgraded) if its rating as of a given reference date is lower (higher) than its rating as of twelve months prior to that reference date on the basis of ratings with numeric modifiers.

Downgrade (Upgrade) Rate

The downgrade (upgrade) rate is the number of downgraded (upgraded) issuers divided by the number of issuers with ratings outstanding during the twelve month reference period.

Financial Ratios

Total Debt:

The sum of Long-Term Debt (total) and Debt in Current Liabilities. For detailed definitions, please see COMPUSTAT manual.

Coverage Ratio:

(EBIT + 1/3 Rent) / (Interest Expense + 1/3 Rent + (Preferred Dividends / 0.65))

Leverage Ratio:

Adjusted Debt / Adjusted Capital

Liquidity Ratio:

Cash & Equivalents / Total Assets

Cash Flow to Debt Ratio:

Retained Cash Flow / Adjusted Debt

Rating Drift

The rating drift is the difference between upgraded issuers multiplied by the number of notches upgraded and downgraded issuers multiplied by the number of notches downgraded divided by the number of issuers with ratings outstanding during the corresponding twelve month reference period.

Rating Volatility

The rating volatility is the sum of upgraded issuers multiplied by the number of notches upgraded and downgraded issuers multiplied by the number of notches downgraded divided by the number of issuers with ratings outstanding during the corresponding twelve month reference period.

XI. Related Research

Special Comment:

Rapidly-Evolving Dynamics of Today's Private Banking Industry, March 2001, #65225

Rating Methodology:

Moody's Analytical Framework for Operational Risk Management of Banks, January 2003, #77083

Industry Outlook:

Banking System Outlook: Switzerland, November 2002, # 76659

To access any of these reports, click on the entry above. Note that these references are current as of the date of publication of this report and that more recent reports may be available. All research may not be available to all clients.

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