

SECTOR IN-DEPTH

28 April 2016

Rate this Research >>

TABLE OF CONTENTS

Introduction	2
Data Sample	2
EDF level: Setting the Optimal EDF Trigger Level	2
Going Beyond EDF Level: Additional Signals of Impending Credit Distress	7
Putting It All to Work in Practice	10

Contacts

Danielle Ferry 212-553-7781
Sr Director-Research
 danielle.ferry@moody's.com

Irina Baron 1.212.553.4307
Associate Director
 irina.baron@moody's.com

David Hamilton 65.6511.4650
MD-APAC Sales
 david.hamilton@moody's.com

ABOUT CAPITAL MARKETS RESEARCH

Analyses from Moody's Capital Markets Research, Inc. (CMR) focus on explaining signals from the credit and equity markets. The publications address whether market signals, in the opinion of the group's analysts, accurately reflect the risks and investment opportunities associated with issuers and sectors. CMR research thus complements the fundamentally-oriented research offered by Moody's Investors Service (MIS), the rating agency.

CMR is part of Moody's Analytics, which is one of the two operating businesses of Moody's Corporation. Moody's Analytics (including CMR) is legally and organizationally separated from Moody's Investors Service and operates on an arm's length basis from the ratings business. CMR does not provide investment advisory services or products.

VIEWPOINTS

Using EDF Measures to Identify At-Risk Names – A Monitoring & Early Warning Toolkit

Summary

Moody's Analytics' Public Firm EDF™ (Expected Default Frequency) credit measures are forward-looking probabilities of default, available on a daily basis, for over 42,000 corporate and financial firms, globally, with publicly traded equity. Like fundamental credit analysis, the EDF model quantifies business and financial risk, but unlike fundamental credit analysis, it employs both balance sheet information and financial market data to determine default risk. The market value-based approach of the EDF model benefits from the forward-looking nature of financial markets and markets' real-time updating of companies' expected future cash flows. As a result, EDF measures provide timely warning of changes in credit risk. Regular model validation demonstrates the power of EDF measures to rank order firms by default risk, to signal credit distress well before default, and, in the aggregate, to be consistent with the level of observed default rates. In this report, we outline a practical approach for using EDF measures to effectively monitor large portfolios of firms and proactively identify at-risk names. The Early Warning Toolkit, as we call it, recommends tracking five EDF-related metrics associated with elevated default risk:

- » EDF level – whether a company's EDF level exceeds a set threshold
- » EDF change – measured as year-over-year percent change
- » Relative EDF level – EDF level relative to a company's industry peer group median EDF level
- » Relative EDF change – EDF change relative to a company's industry peer group median EDF change
- » Slope of the EDF term structure – whether the term structure is inverted

Moody's Analytics markets and distributes all Moody's Capital Markets Research, Inc. materials. Moody's Capital Markets Research, Inc. is a subsidiary of Moody's Corporation. Moody's Analytics does not provide investment advisory services or products. For further detail, please see the last page.

1. Introduction

Moody's Analytics' Public Firm EDF™ (Expected Default Frequency) credit measures are forward-looking probabilities of default, available on a daily basis, for over 42,000 corporate and financial firms, globally, with publicly traded equity. Like fundamental credit analysis, the EDF model quantifies business and financial risk, but unlike fundamental credit analysis, it employs both balance sheet information and financial market data to determine default risk. The market value-based approach of the EDF model benefits from the forward-looking nature of financial markets, and markets' real-time updating of companies' expected future cash flows. As a result, EDF measures provide timely warning of changes in credit risk.

In this report, we outline a practical approach for using EDF measures to effectively monitor large portfolios of entities and proactively identify firms most likely to default. The Early Warning Toolkit, as we call it, recommends tracking five EDF-related metrics associated with elevated future default risk. It is well established that EDF level is a reliable reflection of expected default risk. However, we go a step further and show how to select EDF level thresholds that allow users to focus costly and scarce resources on a highly targeted selection of the most at-risk names in their portfolios. Then, we establish that EDF change, relative EDF level, relative EDF change, and term structure inversion provide additional signals of impending credit distress, even among firms with similar EDF levels. Finally, we discuss how to apply the Early Warning Toolkit in practice. First, however, we describe our analysis data.

2. Data Sample

The primary data for this study are EDF measures sourced from Moody's Analytics' CreditEdge Plus. For the following analyses, we constructed a sample of global firms with EDF measures from 1999 through 2014 for which we have the most reliable default data. It is reliable in the sense that there should be few "hidden" defaults – defaults that occurred, but that were neither reported nor observed – which could bias our findings. The sample is therefore limited to what we call "Top 90" firms.

These can be thought of conceptually as large firms. More specifically, the "Top 90" subset was identified by first sorting non-financial and financial companies, separately and within geographical region, by size (measured by sales for non-financials, and book assets for financials). Working from the largest to the smallest, we then selected firms consisting of 90% of total outstanding liabilities in each sub-group (by geographical region and by non-financial/financial sector).

In some of our analyses, we compare companies to their peer groups. We define peer groups first by country and industry¹. For example, the peer group of Ford Motor Co. would be the US Automotive Group. Since we utilize peer group medians, it is necessary that a peer group has a minimum number of constituents for a median to be meaningful. If a company's peer group has less than 10 constituents, we assign its peer group by industry alone². The country-industry peer group for British American Tobacco, P.L.C., for example, has only four constituents, and so its peer group is the Global Tobacco Group.

3. EDF Level: Setting the Optimal EDF Trigger Level

Regular model validation demonstrates the power of EDF measures to rank order firms by default risk, to signal credit distress well before default, and, in the aggregate, to be consistent with the level of observed default rates. In other words, there is a clear relationship between the EDF level and the subsequent level of credit risk. As a firm's EDF measure rises, the risk of a future credit event occurring also rises. However, it is not always clear as to where to draw the line. If, for example, a firm's EDF level rises to 1% should one become concerned about material default risk? Expressed differently, should one focus on the top 10% of firms by EDF level in one's portfolio or the top 20%? Setting the proper threshold level saves time and allows portfolio managers and credit analysts to efficiently allocate limited resources for portfolio monitoring.

Consider a hypothetical optimal threshold, which we call t^* . If a company's EDF level exceeds the threshold, t^* , a high likelihood of default is expected, and close monitoring of this entity is recommended. This is represented in the first row and column of Exhibit 1. Moving across this row, there are two possible outcomes: the firm defaults (true positive) or the firm does not default (false positive). An ideal optimal threshold will produce many true positives and few false negatives, as false negatives waste scarce resources. Alternatively, we expect that a company whose EDF level is less than the threshold, t^* , will not default, indicating that close monitoring is not necessary. This is represented in the second row and first column of Exhibit 1. Once again, there are two possible outcomes: default (false positive) or no default (true negative). A false negative, or the unexpected default of a firm, could result in direct credit losses. A good forward-looking credit risk measure minimizes the false negatives and false positives, while at the same time

maximizing the true positives and true negatives. In this section, we describe a method for identifying an effective EDF threshold or set of thresholds that is optimal in that sense.

Exhibit 1

Classification Errors Are a Function of the Threshold

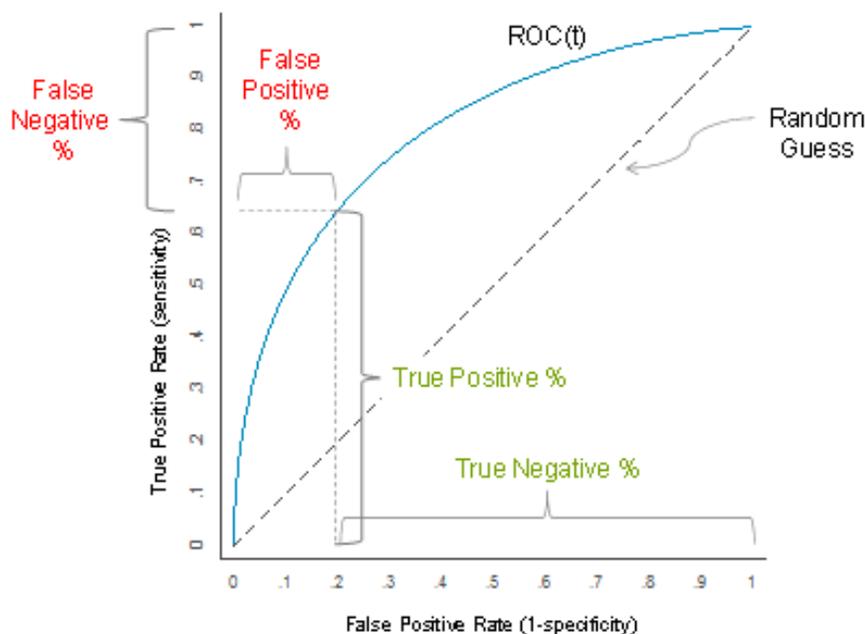
CLASSIFICATION	POSITIVE Default	NEGATIVE No Default
PREDICTED POSITIVE $EDF \geq t^*$	True Positive ✓	False Positive ✗
PREDICTED NEGATIVE $EDF < t^*$	False Negative ✗	True Negative

3.1 Optimal Threshold

The Receiver Operating Characteristic (ROC) curve is a diagnostic graph that illustrates the performance of a predictive binary classifier. The curve, as shown in Exhibit 2, below, is created by plotting the true positive rate against the false positive rate at various threshold settings. The true positive rate, often referred to as sensitivity, is described by the vertical axis. The false positive rate, often referred to as 1-sensitivity, is described by the horizontal axis. The gray dashed 45-degree line in the Exhibit represents the ROC curve for a completely randomly set of thresholds. The least desirable combinations of true positive and false positive rates lie on this line. A perfect threshold lies on the (0, 1) point on the graph, where the true positive rate equals 100% and the false positive rate equals 0%.

Exhibit 2

ROC Curve



If the costs and benefits of classification can be estimated, it is straightforward to calculate economically significant EDF triggers from any given ROC curve. However, in practice, estimating the benefits and costs of classification may be difficult, imprecise, or impossible.

From a practical perspective, a desirable goal would be to attempt to maximize predictive accuracy (where the costs and benefits of true and false positives are weighted equally). To maximize the predictive accuracy of classification we can use either of the following approaches: Youden's Index or the Euclidean method. Each method attempts to derive an optimal threshold derived from historical data. It is optimal in the sense that true positives and negatives are maximized and false positives and negatives are minimized at the given threshold level.

Youden's Index is a statistic that captures the performance of a diagnostic test. The index is defined for all points on the ROC curve as the difference between the true positive rate and the false positive rate. The maximum value of the index, represented as J in Exhibit 3, is the point where the distance between the ROC curve and the Random Guess line is greatest. When we calculated Youden's Index for the data in our sample (across all countries and industries), we found an optimal EDF trigger level of 3.04%. This suggests that portfolio exposures to firms with an EDF measure higher than 3.04% require further analysis. Comparing this trigger level to the overall distribution of EDF measures, we observe that it falls near the 75th percentile of all the firms in our sample³.

Alternatively, the Euclidean method defines the optimal threshold as one that minimizes the distance between the perfect predictor (i.e., the true positive rate equals 100% and the false positive rate equals 0%) and the ROC curve. This distance is represented as d in Exhibit 4, below. Using the Euclidean method, we derive an optimal EDF trigger of 2.65%, which is slightly lower than the 75th percentile of the distribution of EDF measures in our sample.

Exhibit 3

Youden's Index Threshold Calculation for EDF Distribution, Global "Top 90" Firms, 1999-2014

- » We applied the Youden's Index threshold calculation to "top 90" firms with EDFs, globally, between 1999 and 2014
- » Trigger = 3.04
- » EDF, 25th %ile = 0.17
- » EDF, 50th %ile = 0.70
- » EDF, 75th %ile = 3.00
- » EDF, 90th %ile = 9.82

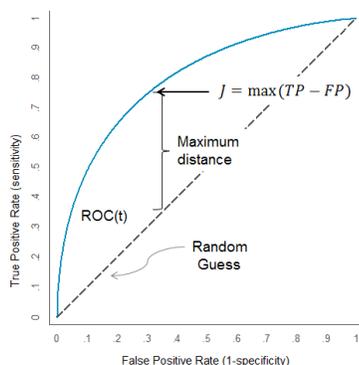
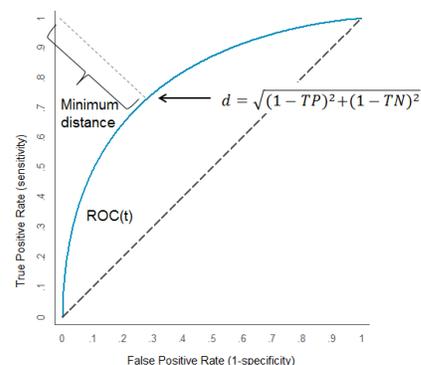


Exhibit 4

Euclidean Method Threshold Calculation for EDF Distribution, Global "Top 90" Firms, 1999-2014

- » We applied the Euclidean method threshold calculation to "top 90" firms with EDFs, globally, between 1999 and 2014
- » Trigger = 2.65
- » EDF, 25th %ile = 0.17
- » EDF, 50th %ile = 0.70
- » EDF, 75th %ile = 3.00
- » EDF, 90th %ile = 9.82



Depending on the sample being analyzed, optimal EDF thresholds dictated by Youden's Index or the Euclidean method may differ somewhat, but not materially overall. For the rest of this paper, we focus on trigger levels derived from Youden's Index.

3.2 Operationalizing the EDF Early Warning Trigger

In practice, it is not sufficient to set a single trigger level, since the level and share of the distribution of EDF measures varies across several key dimensions. Exhibit 5 shows box plots summarizing the distribution of EDF measures of our sample by region: North America, Europe, Japan, and the rest of the world. Each box represents observations between the 25th and 75th percentiles. The blue lines inside each box represent the medians, and the "whiskers" represent the 1st and the 99th percentiles of the distribution. The absolute Youden's Index trigger of 3.04% we derived from the full sample is clearly too high for three out of the four regions, since it lies well above the 99th percentile of the EDF distributions for North America and Europe, and close to but still above the 99th percentile of Japan's EDF distribution.

Similarly, a single trigger would not be appropriate across industry sectors. Exhibit 6 shows that the distribution of EDF measures by industry sectors varies widely. Financial Services, for example, have a much lower and more compressed distribution of EDF measures than other sectors (as one would expect). An absolute trigger of 3.04% would fail to flag nearly any of the risky firms within that sector.

Exhibit 5
EDF Distribution by Region, Global "Top 90" Firms, 1999-2014

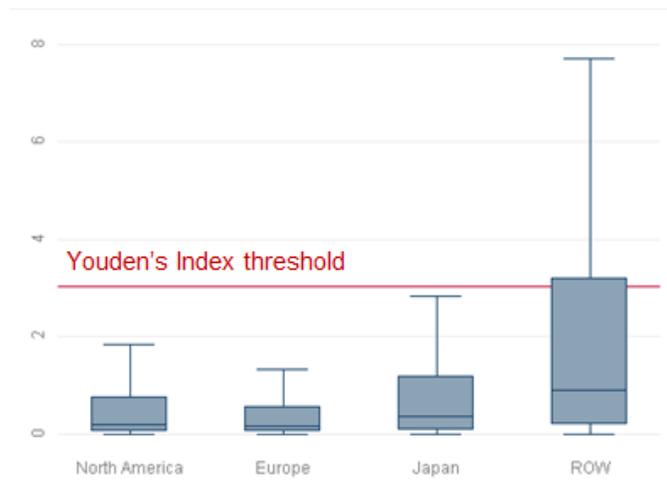
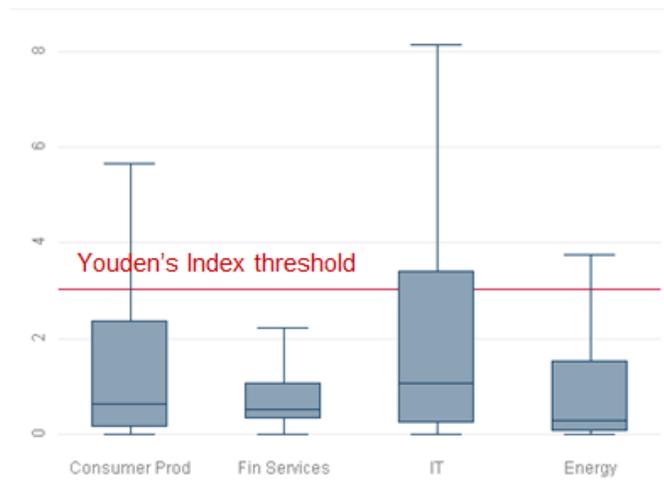


Exhibit 6
EDF Distribution by Select Sectors, Global "Top 90" Firms, 1999-2014



Time is an important dimension to consider, as well, when setting trigger levels. The level of default risk varies significantly over the economic cycle. Exhibit 7 shows the trend in the mean and median EDF measures for global "Top 90" firms from 1999 to 2014. A single EDF trigger of 3.04% (represented as the red horizontal line) will not be effective over time, as it is likely to miss many future defaulters during periods of low default risk and to flag too many names during periods of high default risk. To address this we calculated time-varying triggers, which generally follow the trend of the mean EDF for the overall sample. In Exhibit 7 the optimal time-varying threshold is represented by the red line.

The optimal time varying threshold level exhibits some important characteristics. First, it is highly pro-cyclical – when default risk is rising, the optimal EDF threshold increases, and vice-versa. In an environment of rising aggregate default risk, it becomes difficult to identify which particular firms are relatively more risky because default probabilities for almost all firms are rising. In order to maximize the difference between true and false positives, the optimal threshold must increase when aggregate default risk is increasing. Conversely, in an environment of low default risk, it is relatively easier to prospectively identify which firms are relatively more risky, so the optimal EDF threshold is commensurately lower.

The preceding analyses suggest that an ideal effective monitoring system using EDF measures should specify separate time-varying optimal triggers for each sector/region combination. However, there are too few defaults to calculate Youden's Index at this level of granularity.

In order to operationalize the EDF trigger, we first calculated a time-varying trigger, separately, for non-financial and financial firms. Next, for each of these sub-samples, we regressed the log of median EDF on the log of the time-varying trigger. In Exhibits 8 and 9, we label the latter the "unadjusted" trigger. As shown in the scatter plots, there is a strong linear relationship between these two variables. These two regressions each produced two estimated parameters - α and β – that describe the long-run relationship between median EDF and the unadjusted, optimal time-varying triggers obtained via Youden's Index. The dashed red lines, shown in the line charts in Exhibits 8 and 9 below, represent the adjusted, time-varying triggers for non-financial and financial firms, which have been calibrated from our estimates of the long-term relationship between median EDF levels and optimal EDF trigger levels. The trends of the adjusted triggers generally follow or are higher than the mean EDF values for each sub-sample, as we would expect.

The approach we have developed for deriving sector specific time-varying optimal EDF thresholds has two benefits. First, it smooths out undesirable volatility in the unadjusted, time-varying triggers. Second, it allows us to calculate triggers in real-time, for each of our industry groups. To do this, we apply the estimated parameters, α and β , to median EDF measures for each industry. The 10 industries identified as primarily involved in financial activities are combined into one for this exercise⁴. The parameters from the sample of non-

financial companies are used, separately, for each of the other 51 industries. The result yields 52 different industry-specific triggers at any given time.

Exhibit 7
Time-Varying Trigger vs Mean and Median EDF, Global "Top 90" Firms, 1999-2014

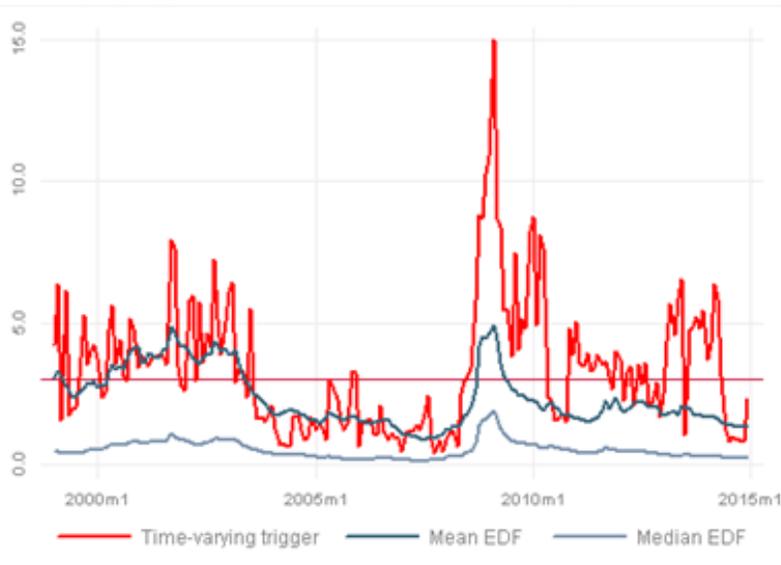


Exhibit 8
Median EDF vs Unadjusted Trigger (scatter plot) and Adjusted Trigger for Financials (line chart)

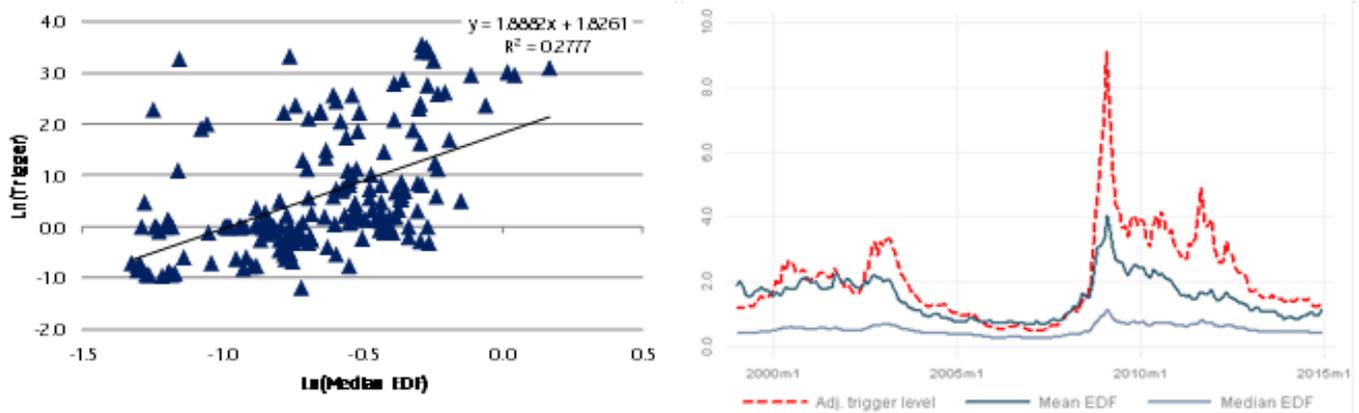
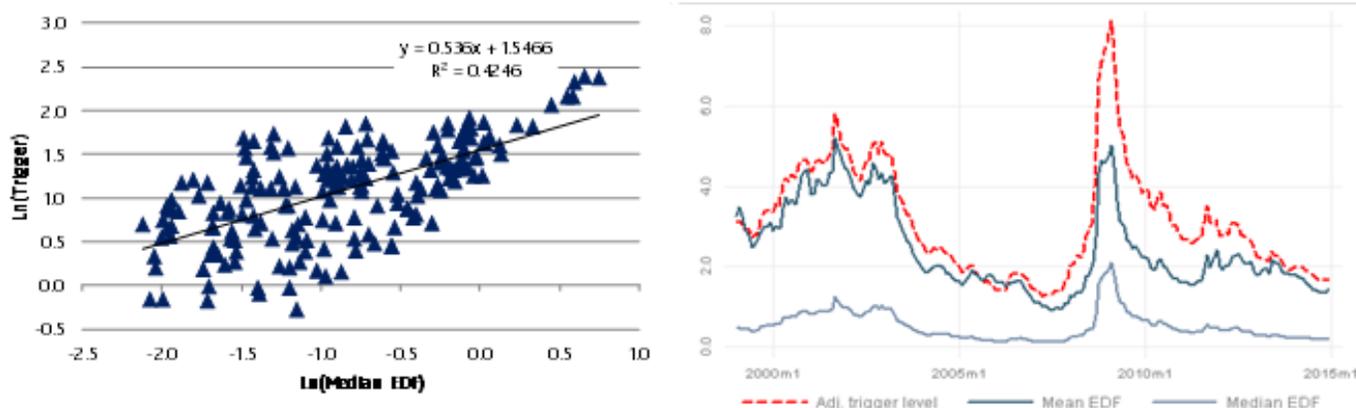


Exhibit 9

Median EDF vs Unadjusted Trigger (scatter plot) and Adjusted Trigger for Non-Financials (line chart)



4. Going Beyond EDF Level: Additional Signals of Impending Credit Distress

EDF level is strongly positively predictive of default risk. In the last section, we described a way to set thresholds, or trigger levels, that allow EDF users to accurately and proactively identify at-risk names in an efficient manner. In this section, we consider several other metrics that also signal rising default or downgrade risk, even among firms with similar EDF levels. These metrics are especially useful when one wishes to discriminate among the highest EDF names.

To uncover the added benefit of each metric, we first divided our sample of global “Top 90” firms into quartiles, by EDF level. Then we further divided each quartile into four equal-sized buckets by: EDF change, relative EDF level, or relative EDF change. In the last section, we split each EDF quartile into firms with inverted EDF term structures and firms with normal, or upward sloping term structures. We examine each of these metrics in greater detail in sections 4.1 through 4.4.

4.1 EDF Change

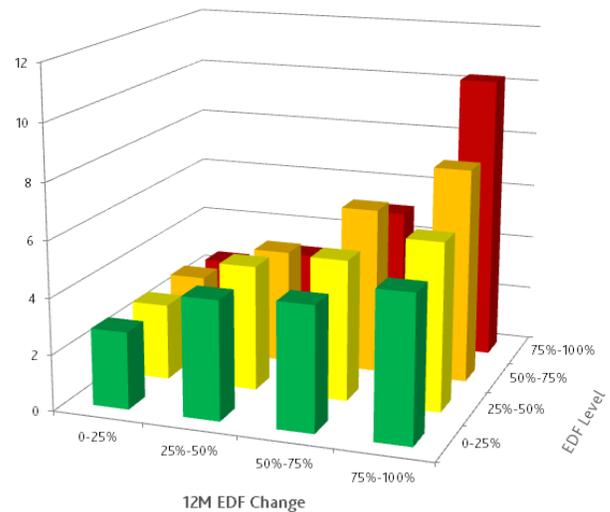
We define EDF change as the percent change in the EDF measure over the last 12 months. Exhibit 10 shows one-year empirical default rates, by EDF quartile, by EDF change quartile, and within each combination of EDF level and EDF change quartile⁵. As shown in the last column, default risk rises as EDF level rises. The bottom row demonstrates that default risk also rises as EDF change rises. Looking within each EDF level quartile (any of the first four rows), we notice that default risk rises as EDF change increases even among firms with similar EDF levels. This is particularly noticeable in the third and fourth EDF level quartiles. In other words, looking at EDF change in addition to EDF level alone, provides even more benefit to an already strong signal of default risk.

As shown in Exhibit 11, a deteriorating EDF trend also signals higher rating downgrade risk – overall, and within EDF level quartile. The z-axis in Exhibit 11 represents the EDF level quartiles, the x-axis represents the EDF change, and the heights of the colored bars represent the one-year downgrade rate for Moody’s long-term ratings. Looking at the chart, as EDF level rises (from front to back) the bars representing the downgrade rate rise accordingly. Additionally, the EDF change quartiles, which increase from left to right, show that as EDF change rises, downgrade rates rise, the likelihood of a rating downgrade also rises, across all the EDF level quartiles.

Exhibit 10
One-Year Default Rates Conditioned on EDF Level and EDF Change, %

EDF Level	EDF Change				All
	0-25%	25%-50%	50%-75%	75%-100%	
0-25%	0.110	0.023	0.026	0.040	0.049
25%-50%	0.214	0.123	0.173	0.172	0.171
50%-75%	0.322	0.324	0.475	0.434	0.389
75%-100%	1.623	2.125	3.040	4.871	2.912
All	0.538	0.595	0.863	1.265	0.815

Exhibit 11
One-Year Rating Downgrade Rate Conditioned on EDF Level and EDF Change, %



4.2 Relative EDF Level

Relative EDF level is calculated as the ratio of each firm's EDF measure to the median EDF measure of its industry peer group. For example, a relative EDF level of two means that a firm's EDF level is twice as high as the median for its peer group. Peer groups are defined by country and industry (e.g., US Automotive Group), or if that group has less than 10 constituents, just industry (e.g., Global Automotive Group). On average, firms with EDF levels higher than the median EDF of their industry peer group are 10 times more likely to default than their peers.

The magnitude of increased default risk among firms with high relative EDF levels is dampened, but not eliminated, once we control for EDF level. As Exhibit 12 shows, one-year observed default rates rise with relative EDF levels, within EDF level quartiles. This is particularly apparent among the highest EDF level firms, as represented by the red colored bars.

The results are similar for rating downgrade rates. As EDF level rises, downgrade risk rises. And, as relative EDF level rises (shown in Exhibit 13 as a move on the x-axis from left to right) downgrade risk rises, within all EDF level quartiles.

Exhibit 12
One-Year Default Rates Conditioned on EDF Level and Relative EDF Level, %

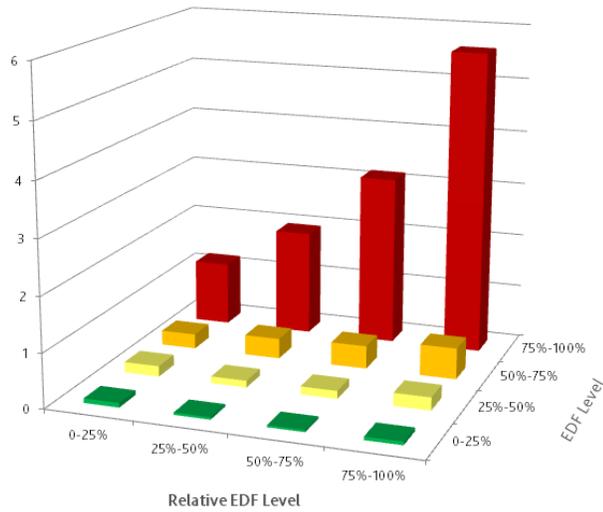
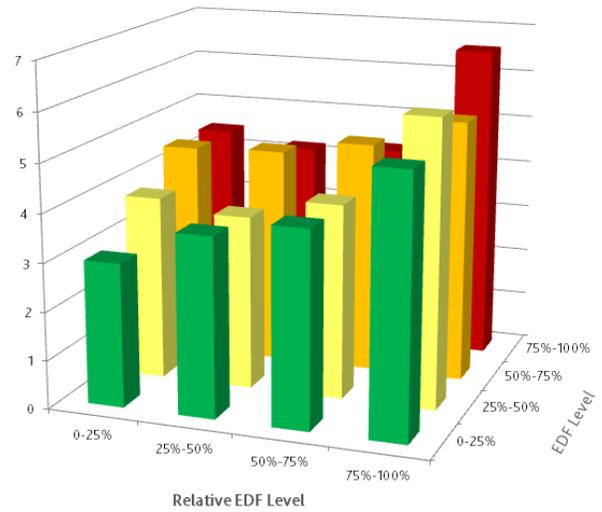


Exhibit 13
One-Year Rating Downgrade Rates Conditioned on EDF Level and Relative EDF Level, %



4.3 Relative EDF Change

Relative EDF change is the one-year change in each firm's EDF level less that of its industry peer group's median EDF change ($\Delta EDF[i] - \Delta EDF[G]$). On average, firms with EDF changes greater than the changes in the median EDF of their industry peer group are more than twice as likely to default than their peers. Looking within EDF level quartile, we still observe the relationship that the higher the relative EDF change, the higher are observed default and rating downgrade rates (Exhibits 14 and 15).

Exhibit 14
One-Year Default Rates Conditioned on EDF Level and Relative EDF Change, %

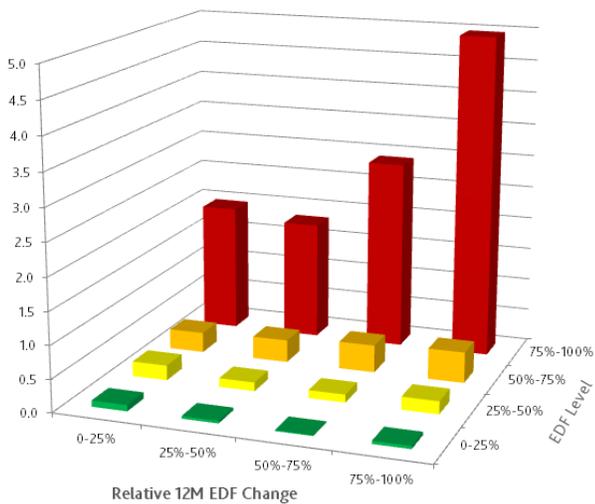
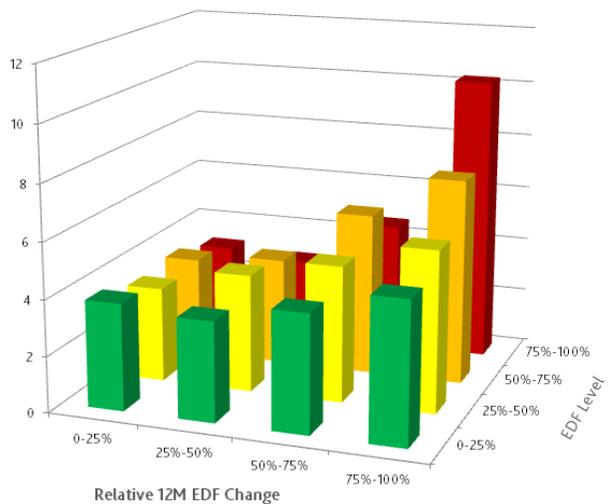


Exhibit 15
One-Year Rating Downgrade Rates Conditioned on EDF Level and Relative EDF Change, %



4.4 Slope of the EDF Term Structure

Moody's Analytics produces annualized EDF measures with one-year to ten-year time horizons. The EDF term structure recognizes that systematic factors play a relatively larger role in a company's default risk over a shorter horizon, while idiosyncratic risk plays a relatively larger role over a longer horizon. Longer horizon EDF measures, therefore, are more stable over time than shorter horizon EDF measures. Together, the three components to the EDF term structure – a long-run, central default tendency, an aggregate factor, and a firm-specific factor – capture these concepts. EDF term structures are typically steeper during economic expansions and flatter during recessions. In general, low-risk firms have upward sloping term structures that invert when risk increases; high-risk firms have downward sloping term structures.

When a firm's five-year EDF measure is lower than its one-year EDF measure, we describe its term structure as inverted. Intuitively, an inverted EDF term structure implies that a firm is more likely to default in the near term than over the longer term, assuming it survives to the longer term. On average, firms with inverted EDF term structures are 13 times more likely to default than firms with upward sloping (normal) term structures. Exhibit 16 shows one-year observed default rates conditioned on EDF level and EDF term structure slope. The empirical default rate, represented by the red bar, is higher even when controlling for EDF level. The effect is especially pronounced for firms in the quartile with the highest EDF levels. The combination of a relatively high EDF level and an inverted EDF term structure is associated with an empirical default rate five times higher than if the EDF term structure were upward sloping. An inverted term structure also signals higher risk of rating downgrade (Exhibit 17), particularly for firms with relatively low EDF levels.

Exhibit 16

One-Year Default Rates Conditioned on EDF Level and EDF Term Structure Inversion, %

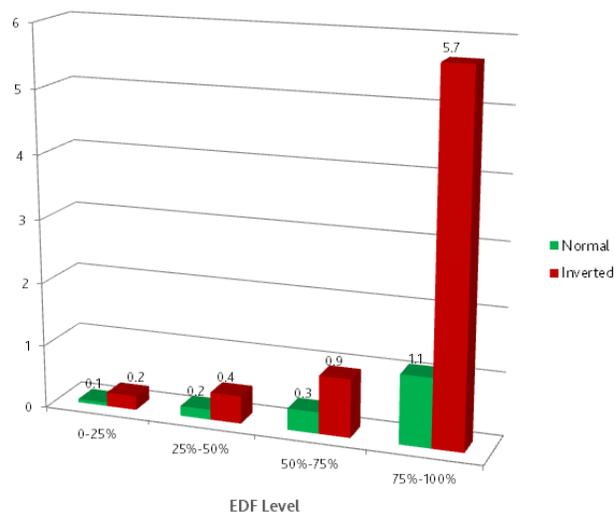
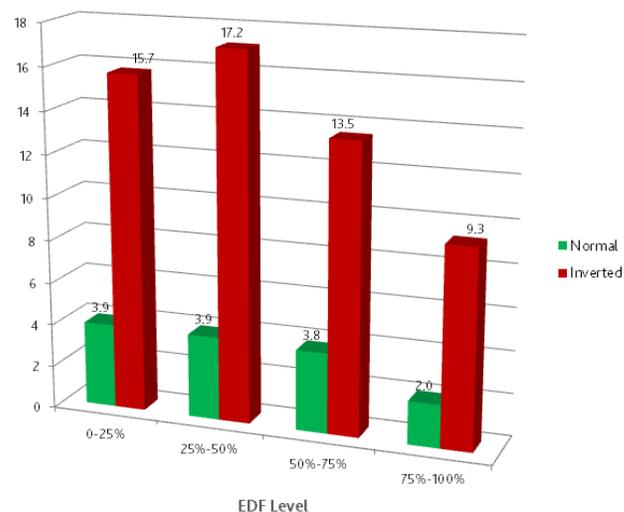


Exhibit 17

One-Year Rating Downgrade Rates Conditioned on EDF Level and EDF Term Structure Inversion, %



5. Putting It All to Work in Practice

EDF data and a wide variety of analytic tools are available via CreditEdge Plus. Many of these tools, such as custom portfolios and alerts can be leveraged to put the EDF Early Warning Toolkit into practice. Additionally, to help users efficiently analyze exposures in their portfolios and to use the early warning metrics discussed in this paper, we have created an EDF Early Warning Toolkit Excel template that utilizes the CreditEdge Excel Add-In. The template offers a way to quickly and easily identify which portfolio exposures warrant further review. Each of the primary columns in the Excel spreadsheet corresponds to the five metrics highlighted in the Early Warning Toolkit. Color coding indicates whether a company warrants further review on the basis of each individual metric as well as overall. For example, the aggregate company risk score for Petroshale, Inc., shown in the last column of Exhibit 18, is highlighted in red, signaling that on the basis of the combination of these metrics the firm exhibits relatively high default risk and requires additional attention. Petroshale's EDF level (as compared to the trigger level for global oil companies), term structure, and relative EDF level are signaling a high degree of distress. Its EDF change signals a moderately high level of distress. Only its relative EDF change appears normal.

Names with aggregate company risk scores highlighted in orange or even yellow may warrant additional review, depending on a user's degree of risk aversion and available resources. The EDF Early Warning Toolkit is an easy to use and powerful addition to the portfolio monitoring process.

Exhibit 18

Excel Template for the EDF Early Warning Toolkit

Moody's ANALYTICS		CreditEdge					
Quickly identify at-risk names in your portfolio based on 5 metrics: EDF level, EDF term structure, EDF change, relative EDF level, and relative EDF change.							
1. Enter up to 1000 company identifiers in cells B16 to B1015. 2. Enter a date for which to view current values in cell D10. 3. Enter a lookback period in cell D11.							
Current Date:		4/20/2016					
Lookback Period		12 months					
Previous Date		4/17/2015					
Enter Identifiers Below:	Company Name	Current 1Y EDF	Current 5Y EDF - 1Y EDF (bps)	Current EDF %Δ	Current Relative EDF	Current Relative EDF %Δ	Aggregate Company Risk Score
ma_id-N07067	NII HOLDINGS INC	2.14%	445.08	-95.72%	2.42	-144.20%	0.25
ma_id-N04797	DEX MEDIA INC	18.19%	-238.75	-63.62%	13.34	-133.40%	0.70
ma_id-N04938	CENTRUS ENERGY CORP	45.25%	-1230.12	15.94%	113.74	-112.43%	0.75
ma_id-346091	FOREST OIL CORP -OLD	50.00%	-1574.87	0.00%	4.41	-168.69%	0.75
ma_id-89614J	DYNEGY INC	3.43%	-137.06	626.94%	0.30	458.25%	0.70
ma_id-W03021	ALPHA BANK SA	4.69%	71.03	4.73%	8.62	-3.57%	0.65
ma_id-G12818	BANCO SANTANDER SA	0.81%	87.07	86.06%	1.48	77.75%	0.50
ma_id-G13317	TOYOTA MOTOR CORPORATION	0.10%	26.41	71.85%	0.25	-6.20%	0.35
ma_id-G12952	WESTPAC BANKING CORPORATION	0.42%	93.95	42.27%	0.96	32.26%	0.40
ma_id-W12982	DAIMLER AG	0.19%	45.91	158.25%	1.29	56.55%	0.55
ma_id-G10187	FUJITSU LIMITED	0.20%	39.91	425.06%	0.46	410.41%	0.50
ma_id-W61335	NVH KOREA INC	3.15%	344.98	147.34%	4.56	112.03%	0.60
ma_id-W44218	CELLCOM ISRAEL LTD.	0.54%	159.64	-76.12%	0.91	-59.06%	0.25
ma_id-W35674	AIR CHINA LIMITED	1.11%	147.61	255.55%	2.64	167.76%	0.55
ma_id-W50200	CARBOCHIM SA	3.50%	541.97	-45.45%	1.04	-43.83%	0.30
ma_id-W37981	VERIMARK HOLDINGS LTD	6.30%	491.95	-25.29%	11.02	-80.03%	0.55
ma_id-G10327	VOLKSWAGEN AG	0.48%	43.48	548.64%	3.23	446.93%	0.60
ma_id-N06330	SUN LIFE FINANCIAL INC	0.36%	64.92	21.39%	0.89	15.71%	0.35
ma_id-N22808	PETROSHALE INC	40.39%	-1109.87	46.98%	3.56	-121.71%	0.80
ma_id-N09345	JUST ENERGY GROUP INC	0.65%	68.72	-24.45%	1.04	-163.85%	0.25
ma_id-628855	BANK OF AMERICA CORP	0.27%	49.60	43.71%	0.87	33.49%	0.40
ma_id-G13187	INTESA SANPAOLO SPA	0.85%	100.09	5.86%	1.57	-2.45%	0.40
ma_id-W12982	DAIMLER AG	0.19%	45.91	158.25%	1.29	56.55%	0.55
ma_id-W08383	HEXAGON AB	0.02%	18.84	5.43%	0.08	-207.16%	0.20
ma_id-W28449	CHINA ASSETS (HOLDINGS) LIMITED	0.36%	107.51	104.29%	0.82	78.22%	0.45
ma_id-N20013	APOLLO GLOBAL MANAGEMENT LLC	0.28%	73.33	-63.17%	0.77	-91.01%	0.20
ma_id-N03932	YUM BRANDS INC	0.06%	18.24	53.01%	0.32	-15.51%	0.40
ma_id-428040	HERTZ GLOBAL HOLDINGS INC	1.74%	51.06	449.67%	2.01	391.09%	0.75
ma_id-277461	EASTMAN KODAK CO	2.83%	23.33	331.76%	16.39	369.24%	0.60
ma_id-W00637	PETROLEO BRASILEIRO SA PETROBRAS	12.16%	-351.43	101.98%	19.65	46.20%	0.90
ma_id-W34979	ALOK INDUSTRIES LTD	14.52%	152.93	50.15%	4.15	78.71%	0.75

Endnotes

- [1](#) There are 61 industry classifications.
- [2](#) This has little impact on companies in North America, Western Europe, and Southeast Asia.
- [3](#) We can gain a greater intuitive understanding of the meaning of this optimal threshold by comparing it to the empirical default rates of companies rated by Moody's Investors Service. At a one year time horizon, a 3.04% default rate is consistent with a B1 long-term rating. In other words, across firms in all industries in countries in our data set, if a firm's EDF measure were to rise to a level consistent with a B1 rating it can be expected to exhibit heightened risk of default over the next year.
- [4](#) These are: Banks and S&Ls, Finance Companies, Finance NEC, Insurance-Life, Insurance-Prop/Cas/Health, Investment Management, Lessors, Real Estate, Real Estate Investment Trusts, and Security Brokers & Dealers.
- [5](#) It is worth emphasizing that EDF levels are measured at a point in time, and empirical default rates are measured one year after that date. The results in Exhibits 10 and 11 highlight the predictive power of EDF levels and EDF changes.

© 2016 Moody's Corporation, Moody's Investors Service, Inc., Moody's Analytics, Inc. and/or their licensors and affiliates (collectively, "MOODY'S"). All rights reserved.

CREDIT RATINGS ISSUED BY MOODY'S INVESTORS SERVICE, INC. ("MIS") AND ITS AFFILIATES ARE MOODY'S CURRENT OPINIONS OF THE RELATIVE FUTURE CREDIT RISK OF ENTITIES, CREDIT COMMITMENTS, OR DEBT OR DEBT-LIKE SECURITIES, AND CREDIT RATINGS AND RESEARCH PUBLICATIONS PUBLISHED BY MOODY'S ("MOODY'S PUBLICATIONS") MAY INCLUDE MOODY'S CURRENT OPINIONS OF THE RELATIVE FUTURE CREDIT RISK OF ENTITIES, CREDIT COMMITMENTS, OR DEBT OR DEBT-LIKE SECURITIES. MOODY'S DEFINES CREDIT RISK AS THE RISK THAT AN ENTITY MAY NOT MEET ITS CONTRACTUAL, FINANCIAL OBLIGATIONS AS THEY COME DUE AND ANY ESTIMATED FINANCIAL LOSS IN THE EVENT OF DEFAULT. CREDIT RATINGS DO NOT ADDRESS ANY OTHER RISK, INCLUDING BUT NOT LIMITED TO: LIQUIDITY RISK, MARKET VALUE RISK, OR PRICE VOLATILITY. CREDIT RATINGS AND MOODY'S OPINIONS INCLUDED IN MOODY'S PUBLICATIONS ARE NOT STATEMENTS OF CURRENT OR HISTORICAL FACT. MOODY'S PUBLICATIONS MAY ALSO INCLUDE QUANTITATIVE MODEL-BASED ESTIMATES OF CREDIT RISK AND RELATED OPINIONS OR COMMENTARY PUBLISHED BY MOODY'S ANALYTICS, INC. CREDIT RATINGS AND MOODY'S PUBLICATIONS DO NOT CONSTITUTE OR PROVIDE INVESTMENT OR FINANCIAL ADVICE, AND CREDIT RATINGS AND MOODY'S PUBLICATIONS ARE NOT AND DO NOT PROVIDE RECOMMENDATIONS TO PURCHASE, SELL, OR HOLD PARTICULAR SECURITIES. NEITHER CREDIT RATINGS NOR MOODY'S PUBLICATIONS COMMENT ON THE SUITABILITY OF AN INVESTMENT FOR ANY PARTICULAR INVESTOR. MOODY'S ISSUES ITS CREDIT RATINGS AND PUBLISHES MOODY'S PUBLICATIONS WITH THE EXPECTATION AND UNDERSTANDING THAT EACH INVESTOR WILL, WITH DUE CARE, MAKE ITS OWN STUDY AND EVALUATION OF EACH SECURITY THAT IS UNDER CONSIDERATION FOR PURCHASE, HOLDING, OR SALE.

MOODY'S CREDIT RATINGS AND MOODY'S PUBLICATIONS ARE NOT INTENDED FOR USE BY RETAIL INVESTORS AND IT WOULD BE RECKLESS FOR RETAIL INVESTORS TO CONSIDER MOODY'S CREDIT RATINGS OR MOODY'S PUBLICATIONS IN MAKING ANY INVESTMENT DECISION. IF IN DOUBT YOU SHOULD CONTACT YOUR FINANCIAL OR OTHER PROFESSIONAL ADVISER.

ALL INFORMATION CONTAINED HEREIN IS PROTECTED BY LAW, INCLUDING BUT NOT LIMITED TO, COPYRIGHT LAW, AND NONE OF SUCH INFORMATION MAY BE COPIED OR OTHERWISE REPRODUCED, REPACKAGED, FURTHER TRANSMITTED, TRANSFERRED, DISSEMINATED, REDISTRIBUTED OR RESOLD, OR STORED FOR SUBSEQUENT USE FOR ANY SUCH PURPOSE, IN WHOLE OR IN PART, IN ANY FORM OR MANNER OR BY ANY MEANS WHATSOEVER, BY ANY PERSON WITHOUT MOODY'S PRIOR WRITTEN CONSENT.

All information contained herein is obtained by MOODY'S from sources believed by it to be accurate and reliable. Because of the possibility of human or mechanical error as well as other factors, however, all information contained herein is provided "AS IS" without warranty of any kind. MOODY'S adopts all necessary measures so that the information it uses in assigning a credit rating is of sufficient quality and from sources MOODY'S considers to be reliable including, when appropriate, independent third-party sources. However, MOODY'S is not an auditor and cannot in every instance independently verify or validate information received in the rating process or in preparing the Moody's Publications.

To the extent permitted by law, MOODY'S and its directors, officers, employees, agents, representatives, licensors and suppliers disclaim liability to any person or entity for any indirect, special, consequential, or incidental losses or damages whatsoever arising from or in connection with the information contained herein or the use of or inability to use any such information, even if MOODY'S or any of its directors, officers, employees, agents, representatives, licensors or suppliers is advised in advance of the possibility of such losses or damages, including but not limited to: (a) any loss of present or prospective profits or (b) any loss or damage arising where the relevant financial instrument is not the subject of a particular credit rating assigned by MOODY'S.

To the extent permitted by law, MOODY'S and its directors, officers, employees, agents, representatives, licensors and suppliers disclaim liability for any direct or compensatory losses or damages caused to any person or entity, including but not limited to by any negligence (but excluding fraud, willful misconduct or any other type of liability that, for the avoidance of doubt, by law cannot be excluded) on the part of, or any contingency within or beyond the control of, MOODY'S or any of its directors, officers, employees, agents, representatives, licensors or suppliers, arising from or in connection with the information contained herein or the use of or inability to use any such information.

NO WARRANTY, EXPRESS OR IMPLIED, AS TO THE ACCURACY, TIMELINESS, COMPLETENESS, MERCHANTABILITY OR FITNESS FOR ANY PARTICULAR PURPOSE OF ANY SUCH RATING OR OTHER OPINION OR INFORMATION IS GIVEN OR MADE BY MOODY'S IN ANY FORM OR MANNER WHATSOEVER.

MIS, a wholly-owned credit rating agency subsidiary of Moody's Corporation ("MCO"), hereby discloses that most issuers of debt securities (including corporate and municipal bonds, debentures, notes and commercial paper) and preferred stock rated by MIS have, prior to assignment of any rating, agreed to pay to MIS for appraisal and rating services rendered by it fees ranging from \$1,500 to approximately \$2,500,000. MCO and MIS also maintain policies and procedures to address the independence of MIS's ratings and rating processes. Information regarding certain affiliations that may exist between directors of MCO and rated entities, and between entities who hold ratings from MIS and have also publicly reported to the SEC an ownership interest in MCO of more than 5%, is posted annually at www.moody.com under the heading "Shareholder Relations — Corporate Governance — Director and Shareholder Affiliation Policy."

For Australia only: Any publication into Australia of this document is pursuant to the Australian Financial Services License of MOODY'S affiliate, Moody's Investors Service Pty Limited ABN 61 003 399 657AFSL 336969 and/or Moody's Analytics Australia Pty Ltd ABN 94 105 136 972 AFSL 383569 (as applicable). This document is intended to be provided only to "wholesale clients" within the meaning of section 761G of the Corporations Act 2001. By continuing to access this document from within Australia, you represent to MOODY'S that you are, or are accessing the document as a representative of, a "wholesale client" and that neither you nor the entity you represent will directly or indirectly disseminate this document or its contents to "retail clients" within the meaning of section 761G of the Corporations Act 2001. MOODY'S credit rating is an opinion as to the creditworthiness of a debt obligation of the issuer, not on the equity securities of the issuer or any form of security that is available to retail clients. It would be dangerous for "retail clients" to make any investment decision based on MOODY'S credit rating. If in doubt you should contact your financial or other professional adviser.

For Publications Issued by Moody's Capital Markets Research, Inc. only:

The statements contained in this research report are based solely upon the opinions of Moody's Capital Markets Research, Inc. and the data and information available to the authors at the time of publication of this report. There is no assurance that any predicted results will actually occur. Past performance is no guarantee of future results.

The analysis in this report has not been made available to any issuer prior to publication.

When making an investment decision, investors should use additional sources of information and consult with their investment advisor. Investing in securities involves certain risks including possible fluctuations in investment return and loss of principal. Investing in bonds presents additional risks, including changes in interest rates and credit risk.

Moody's Capital Markets Research, Inc., is a subsidiary of MCO. Please note that Moody's Analytics, Inc., an affiliate of Moody's Capital Markets Research, Inc. and a subsidiary of MCO, provides a wide range of research and analytical products and services to corporations and participants in the financial markets. Customers of Moody's Analytics, Inc. may include companies mentioned in this report. Please be advised that a conflict may exist and that any investment decisions you make are your own responsibility. The Moody's Analytics logo is used on certain Moody's Capital Markets Research, Inc. products for marketing purposes only. Moody's Analytics, Inc. is a separate company from Moody's Capital Markets Research, Inc.

REPORT NUMBER 1024578

Contacts

Danielle Ferry
Sr Director-Research
danielle.ferry@moody's.com

212-553-7781

Irina Baron
Associate Director
irina.baron@moody's.com

1.212.553.4307

David Hamilton
MD-APAC Sales
david.hamilton@moody's.com

65.6511.4650

CLIENT SERVICES

Americas	1-212-553-1653
Asia Pacific	852-3551-3077
Japan	81-3-5408-4100
EMEA	44-20-7772-5454