MOODY'S ANALYTICS

SECTOR IN-DEPTH
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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

## 1. Introduction

Moody's Analytics' Public Firm EDF$^{TM}$(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 industry[1]. 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 alone[2]. 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.

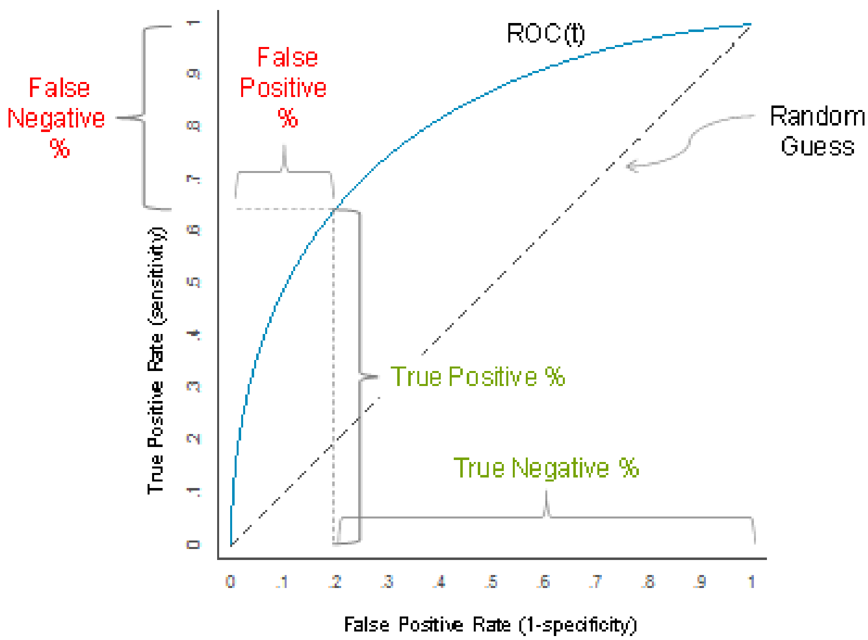
Exhibit 1
**Classification Errors Are a Function of the Threshold**

| CLASSIFICATION | POSITIVE<br>Default | NEGATIVE<br>No Default |
|---|---|---|
| PREDICTED POSITIVE<br>EDF ≥ t* | True Positive √ | False Positive X |
| PREDICTED NEGATIVE<br>EDF < t* | False Negative X | 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 sample[3].

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**

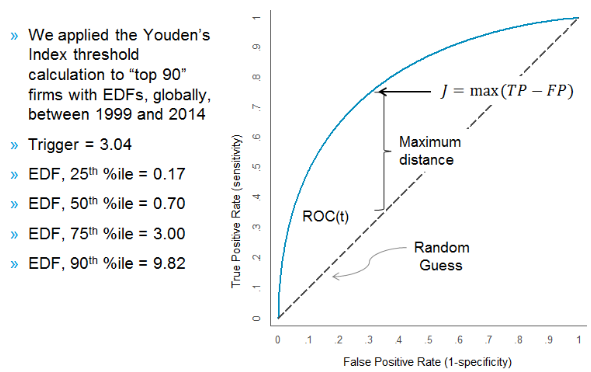
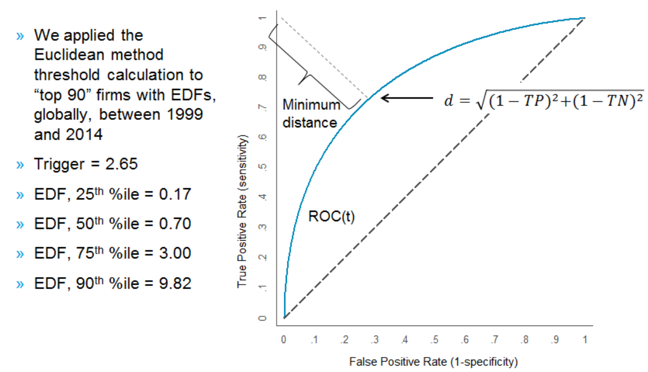



Exhibit 4

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




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**

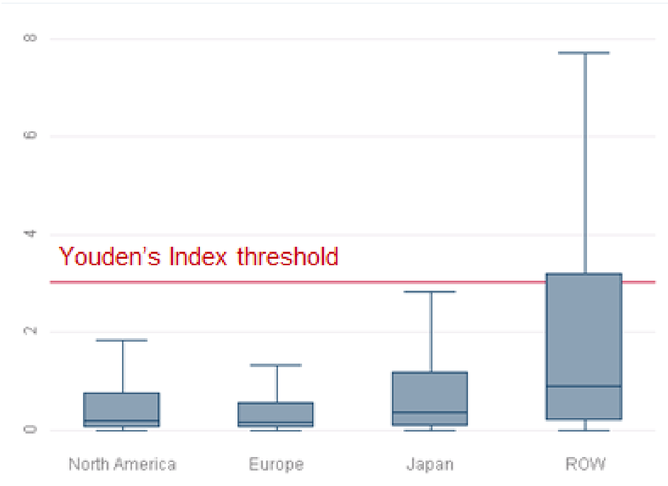
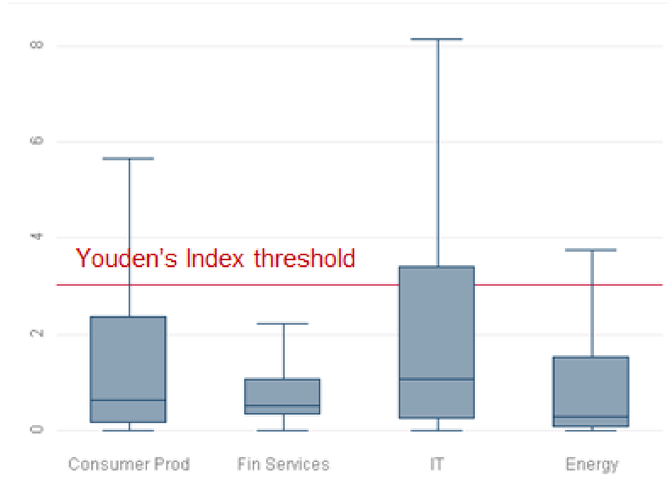



Exhibit 6
**EDF Distribution by Select Sectors, Global "Top 90" Firms, 1999-2014**




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 - $\alpha$ and $\beta$– 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, $\alpha$ and $\beta$, to median EDF measures for each industry. The 10 industries identified as primarily involved in financial activities are combined into one for this exercise[4]. 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**

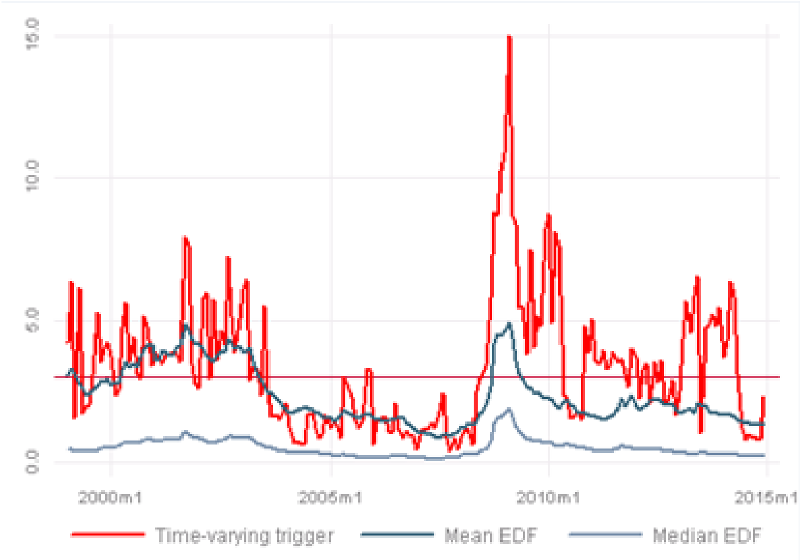
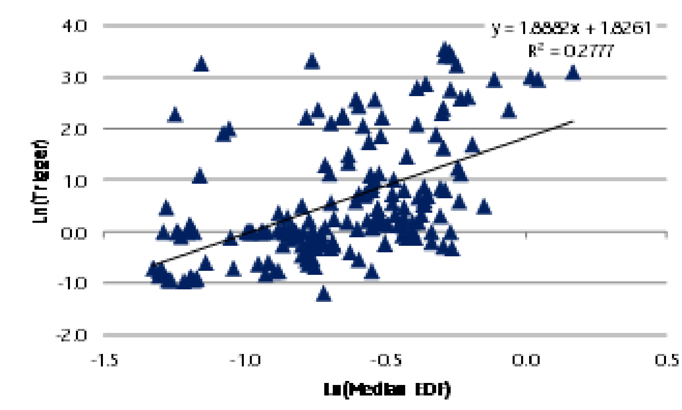



Exhibit 8
**Median EDF vs Unadjusted Trigger (scatter plot) and Adjusted Trigger for Financials (line chart)**



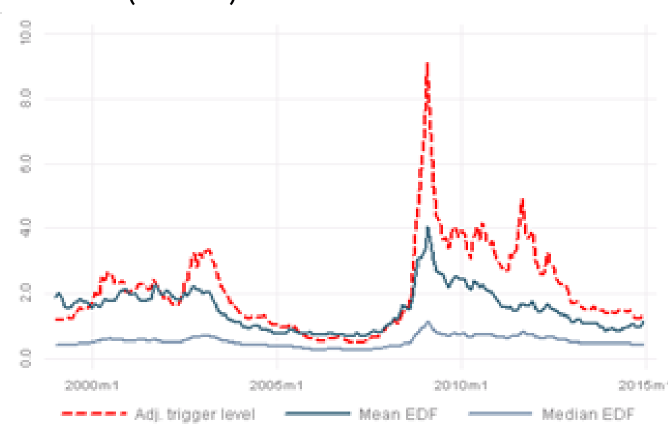
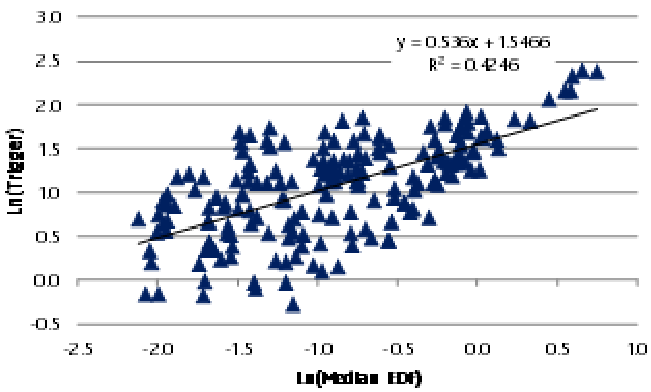
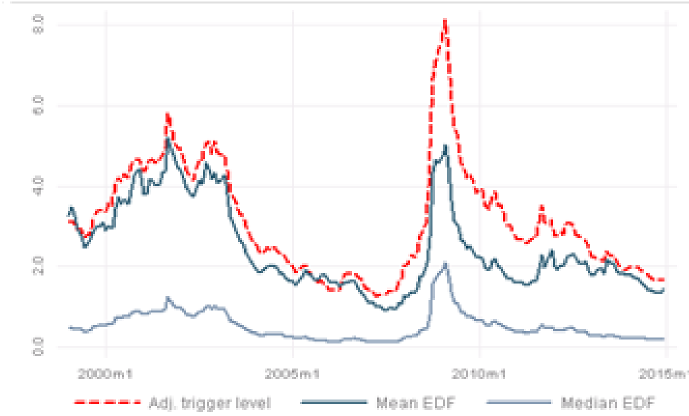



Exhibit 9
**Median EDF vs Unadjusted Trigger (scatter plot) and Adjusted Trigger for Non-Financials (line chart)**




## 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 quartile[5]. 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, %**

Rising EDF Change

Rising EDF Level

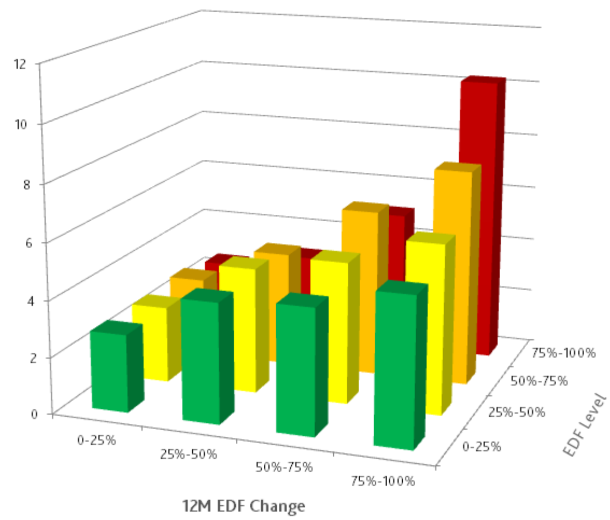
Rising Default Risk

| | EDF Change | | | | |
|---|---|---|---|---|---|
| **EDF Level** | **0-25%** | **25%-50%** | **50%-75%** | **75%-100%** | **All** |
| **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 |

Rising Default Risk

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, %**

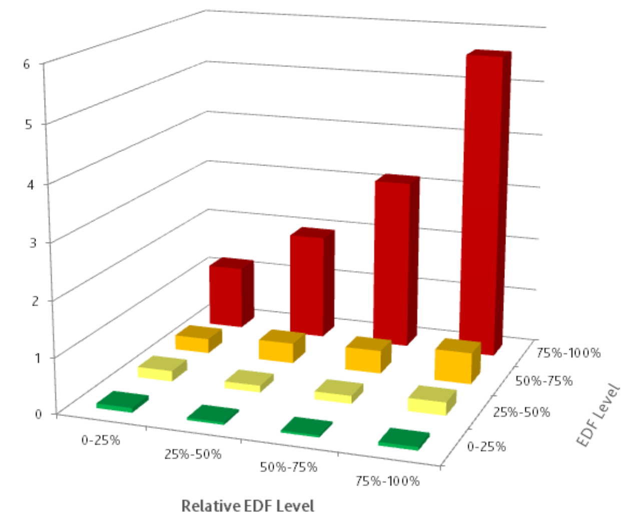
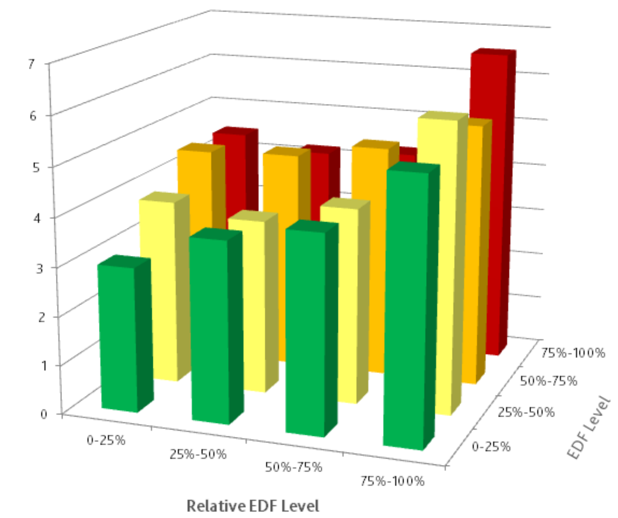



Exhibit 13

**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 (*ΔEDF[i] - ΔEDF[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, %**

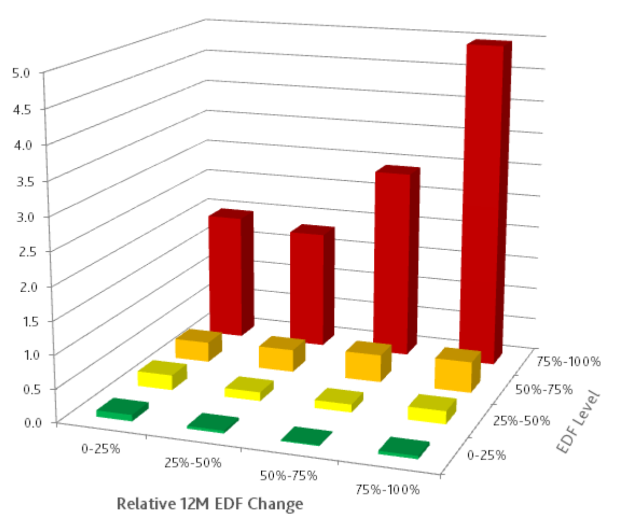
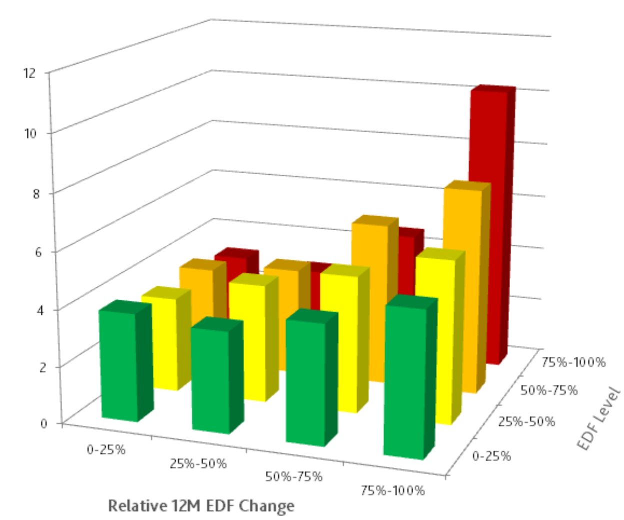



Exhibit 15

**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 EFD 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, %**

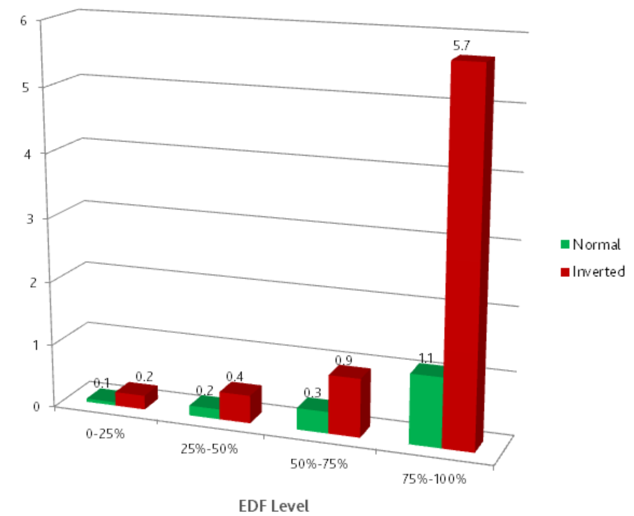
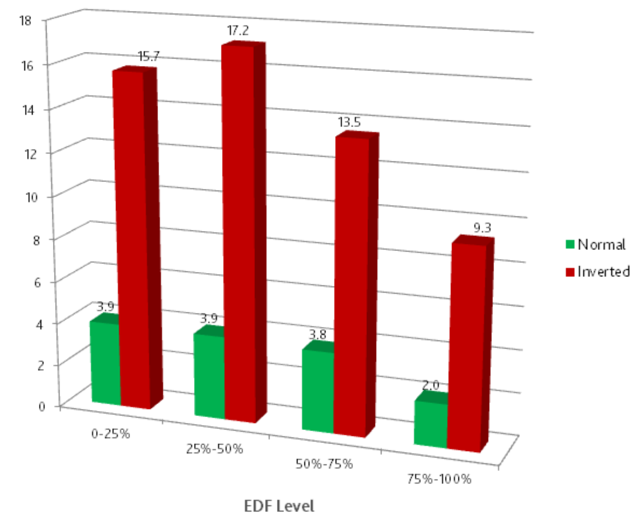



Exhibit 17

**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.

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