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Identifying At-Risk Names in Your Private Firm Portfolio — RiskCalc Early Warning Toolkit

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Abstract

Moody's Analytics RiskCalc™ suite is a collection of geographic- or industry-specific models for private firm default risk measurement. It combines financial statement information and equity market information into a standalone, forward-looking credit risk metric — the RiskCalc EDF™ (Expected Default Frequency) credit measure.

This report outlines a practical approach for using RiskCalc EDF credit measures to effectively monitor large portfolios of private firms and to proactively identify at-risk names. The RiskCalc Early Warning Toolkit Excel add-in is an easy to use, yet comprehensive tool that allows users to focus costly and scarce resources on a highly targeted selection of the most at-risk names in their portfolios. This research for private firms compliments previous research on Early Warning Toolkit for public firms. The Early Warning Toolkit identifies at-risk names within a private firm portfolio well before default, using a number of different EDF-related risk metrics. It is well-established that EDF level is a reliable reflection of expected default risk. In addition to EDF level, relative EDF level, EDF term structure, EDF change, and relative EDF change provide additional information to identify at-risk names. Monitoring and evaluating Trigger-EDF level and deterioration propensity can help enhance the credit monitoring process.

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1. Introduction

Moody's Analytics RiskCalc suite is a collection of geographic- or industry-specific models for private firm default risk measurement. This framework combines financial statement information and equity market information into a standalone, forward-looking credit risk metric — the RiskCalc EDF (Expected Default Frequency) credit measure.

RiskCalc EDF has been used in many different contexts to facilitate many different business decisions. Banks often use RiskCalc EDF measures as an internal rating input or as a constraint on the bank's internal rating. Increasingly, corporates use RiskCalc EDF levels to measure the credit risk of their counterparties and trading partners. RiskCalc EDF helps determine the internal transfer price of credit risk within a large multinational. RiskCalc EDF measures can also be used to allow the transfer of credit risk between unrelated parties in a variety of contexts, including guarantees and surety bonds. Finally, effective use of RiskCalc helps ensure that a thorough and consistent monitoring process is in place at financial institutions.

This report outlines a practical approach for using RiskCalc EDF credit measures to monitor effectively large portfolios of private firms and to proactively identify at-risk names. The RiskCalc Early Warning Toolkit Excel add-in is an easy-to-use, yet comprehensive tool that allows users to focus costly and scarce resources on a highly targeted selection of the most at-risk names in their portfolios. The toolkit identifies at-risk names within a private firm portfolio well before default using a number of different EDF-related risk metrics. The EDF measure has been established as a reliable reflection of expected default risk. However, more insight is often beneficial.

The Early Warning Toolkit (EWTK) tracks five EDF-related metrics and two additional signals associated with elevated default risk:

- EDF level
- Relative EDF level — Percentile ranking of a company's EDF relative to its peers.
- EDF change — Year-over-year percent change in EDF level.
- Relative EDF change — Change in relative EDF level.
- EDF term structure — Whether the term structure is inverted.
- Trigger-EDF level — Whether a company's EDF level exceeds a breakeven threshold.
- Deterioration Propensity — Whether a company's credit risk is increasing.

This paper first establishes that, in addition to EDF level, relative-EDF level, EDF term structure, EDF change, and relative-EDF change provide additional information to identify at-risk names. We next discuss how trigger-EDF level and deterioration propensity can help enhance the credit monitoring process. Finally, we showcase how to apply the Early Warning Toolkit in practice.

2. EDF Risk Metrics

2.1 EDF Level

Moody's Analytics RiskCalc model is the industry standard for estimating private firm default risk. The RiskCalc model estimates the probability of default for private firms using financial statements (income statement and balance sheet), producing the RiskCalc EDF credit measure. In addition to financial statement information, RiskCalc also adjusts for the firm's industry risk and the current stage of the credit cycle. The RiskCalc model calculates an EDF measure at the one- and five-year tenors, and it provides a continuous term structure of EDF values, as well as a forward term structure.

Regular model validation demonstrates the power of RiskCalc EDF measure to rank order firms by default risk, to signal credit distress well before default, and, in the aggregate, to remain consistent with the level of observed default rates.

2.2 Going Beyond EDF Level

RiskCalc EDF level is a powerful standalone metric used to identify default risk. It evaluates a company's default risk at an absolute level — the higher the EDF level, the higher the default risk.

We next consider several other metrics that measure a company's financial health at a relative level — relative to its peers and relative over time. These additional metrics (key components of the Early Warning Toolkit) are useful, especially when discriminating among names with similar EDF levels.

i) Relative EDF Level

We calculate Relative EDF Level as the percentile ranking of a firm's RiskCalc EDF measure compared to its peers in the corresponding model development dataset. For example, we compare a U.S. private firm evaluated by the RiskCalc US 4.0 Corporate Model to all private firms in the U.S. 4.0 Corporate Model development dataset.

RiskCalc model development datasets come from Moody's Analytics Credit Research Database (CRD™). The Credit Research Database is one of the world's largest and most comprehensive financial statement and default databases. Built in partnership with more than 75 leading global financial institutions and vendors, the CRD contains 68+ million financial statements for more than 15 million borrowers, including 1.4 million private company defaults over a long historical time-series (more than two economic cycles) and across many global markets. Comparing a firm's EDF measure to its peers in the development dataset can help position the firm's relative financial strength across peers and over time. The higher the percentile, the higher the firm's RiskCalc EDF level compared to its peers, and, therefore, the higher the company's credit risk relative to its peers.

ii) EDF Term Structure

EDF term structure is an indicator showing whether a firm's term structure is inverted or not.

RiskCalc estimates EDF at both short-time horizon (one-year) and long-time horizon (five-year). 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 the shorter horizon. EDF term structures are typically steeper during economic expansions and flatter during recessions. In addition, we observe that the default rate for "good" firms tends to increase over time, while the default rate for "bad" firms decreases over time, an indication of the mean-reversion effect seen with firms' default risk.

When a firm's short-term EDF surpasses long-term EDF, we describe its term structure as inverted. An inverted term structure indicates that the firm faces elevated risk during the near-term.

iii) EDF Change and Relative EDF Change

We define EDF change and Relative EDF change, respectively, as the percent change in a firm's EDF level over the look-back periods[1] and an indicator showing whether a company's relative EDF is worsening significantly.

While it is important to monitor closely firms with high EDF and Relative EDF levels, it is also worthwhile recognizing that a firm experiencing sharp increases in EDF levels can bring additional, unexpected risks into a portfolio, if not properly monitored as its financial conditions continue to deteriorate, even if its EDF level is low. EDF changes can, therefore, help track the dynamics of the default risk in the portfolio. Similarly, Relative EDF change can help identify firms whose relative financial strength is worsening significantly compared to peers.

[1] Users have the option to choose from different look back periods: 3 months, 6 months, 12 months, etc.

3. Two Additional Signals

Besides the five EDF-related risk metrics, the Early Warning Toolkit also provides two additional signals.

Trigger-EDF Level: EWTK computes a Trigger-EDF level based on pricing information to help users control for economic loss. Trigger-EDF is the EDF level above which a lender would potentially suffer economic loss due to uncompensated default risk. When a firm's EDF level surpasses the Trigger-EDF level, users should consider reviewing loan terms or managing down exposure to the borrower to control for potential losses.

Deterioration Propensity: EWTK aggregates five EDF risk metrics into one additional signal to help clients identify firms whose credit risk is increasing.

3.1 Trigger-EDF Level

i) Methodology

While EDF level is an accurate predictor of default probability, it is not always clear where to draw the line: at which EDF level should the lender start becoming concerned about material loss from the borrower? Should two borrowers priced with different loan terms (spread rate, collateral, etc.) share the same trigger-level?

We believe an optimal trigger-level relates risk to returns. A lender should become concerned if the borrower's default risk becomes higher than what is priced in originally by the loan terms — expected loss from a borrower exceeds expected income, in which case, the lender will potentially end up with negative net profit from the borrower.

In the EWTK, we define the Trigger-EDF level as the break-even EDF measure that equates expected income and expected loss of lending to a borrower. Mathematically, the Trigger-EDF level, EDF^*, satisfies:

$$Expected\ Income\ (EDF^*) = Expected\ Loss(EDF^*)$$

If we assume:[2]

- The expected income of lending to a borrower comes exclusively from interest spread.
- Interest is paid at year-end and the defaulted borrower would not pay accrued interest.

Given annual spread rate[3] and LGD, we have:

$$Expected\ Income\ (EDF) = (1 - EDF) * Spread$$
$$Expected\ Loss\ (EDF) = EDF * LGD$$

The maximum level of default risk (EDF^*) a lender can bear to break-even satisfies:

$$(1 - EDF^*) * Spread = EDF^* * LGD$$

In general, we expect a borrower's EDF level to be lower than the Trigger-EDF level at origination. When a borrower's EDF level rises above the Trigger-EDF level, the expected loss surpasses the expected income, which indicates a high probability of net economic loss.

Within the toolkit, users are encouraged to input their LGD information and their estimate of spread, as users should have the best estimates of such loan-level information. If the information is unavailable, users can refer to pre-populated spread and LGD information calculated based on Moody's CRD database. The pre-populated spread rate is the median spread rate (defined as the annual coupon rate — one-year Libor rate) of more than one million bank loans in the U.S.

[2] We recognize that in actuality, income structure may be far more complicated, with fees or additional relationship benefits, for example. Without loss of generality, we make these assumptions to reduce the complexity of calculations. Users have the option to customize the toolkit to incorporate their judgments on income structure.

[3] Spread and LGD is, in general, loan-specific. For users who have multiple loans with the same borrower, spread/LGD can be computed as the exposure-weighted average of individual spreads/LGDs.

ii) Case Study

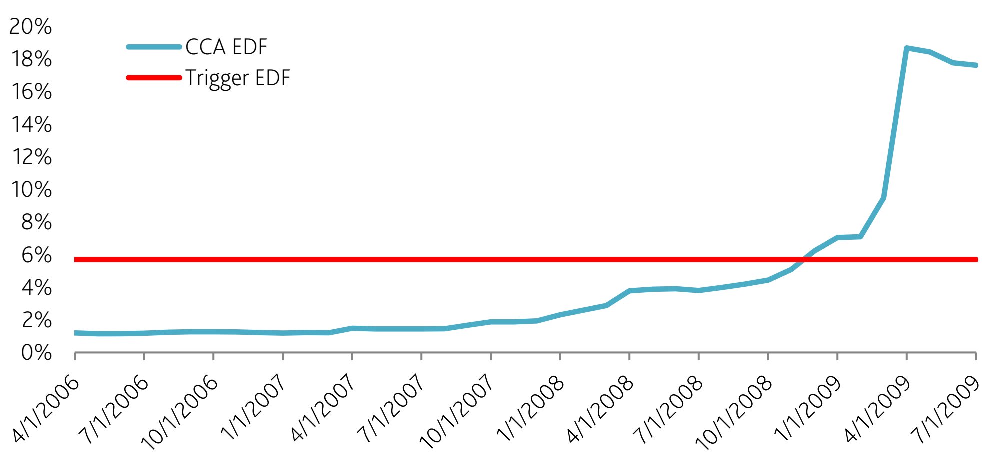
In April 2006, Bank X issues a 20-year term loan with a 2.7% spread over the five-year LIBOR to a retail firm in the mountain states.

The spread rate remains the same since origination. Assuming LGD is 45%, the Trigger-EDF level is 5.7%.

At loan origination, the firm's CCA EDF measure was well below the Trigger-EDF level, meaning the priced-in risk level (Trigger-EDF level) was higher than the actual default risk. At origination, the loan's expected net profit was positive. However, the EDF level continued increasing since origination. By the end of 2008, the CCA EDF measure eventually rose above the Trigger-EDF level. The firm's actual default risk became higher than the break-even default risk, and the expected net profit from the loan became negative. Seven months later, the firm defaulted.

Using EWTK, the bank is notified of the borrower's rising default risk seven months prior to default.

Figure 1 Case Study — Trigger-EDF Level



3.2 Deterioration Propensity

i) Methodology

With public firms, one helpful risk signal is deterioration probability, which measures the downgrade probability of rated firms within a one-year window. The deterioration probability helps identify firms whose credit risk is increasing.

However, generalizing this signal to private firms can be challenging, since private firms are typically not rated. It is difficult to obtain a labeled sample containing private firm downgrade events. Additionally, the lack of powerful predictors such as past downgrade events significantly decreases prediction power for unrated firms.

For users who recognize these challenges, yet are still interested in generalizing this concept to private firms in order to rank order their portfolio across private and public firms based on this concept, we construct a "Deterioration Propensity" metric, which measures the downgrade probability within a one-year window using the rated-firm sample.

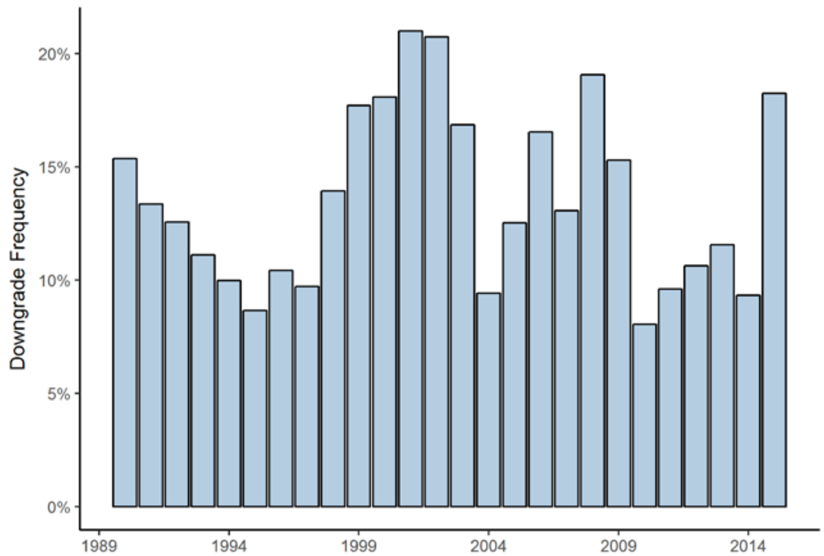
As stated, it is difficult to construct a labeled sample containing downgrade events for private firms. Therefore, we construct a sample of rated firms across countries and compute RiskCalc EDF measures and other EWTK risk metrics for the sample. In total, the sample captures more than 5,400 downgrade events for more than 4,400 rated firms, ranging 1989–2015.

TABLE 1

Data Description

# UNIQUE COUNTRIES	# UNIQUE FIRMS	# UNIQUE OBSERVATIONS	# DOWNGRADE EVENTS	TIME PERIOD
60+	4,400+	39,300+	5,440+	1989-2015

Figure 2 Empirical frequency of downgrade events by year.



To keep the toolkit easy to use, we incorporate the five EWTK risk metrics as raw features. Since the five EWTK risk metrics are all EDF-related, thus correlated, we first conduct principal component analysis[4] to remedy multi-collinearity. Because private firms are mostly unrated, we do not use rating history in the model.

Our modeling process follows three steps:

1) Conduct principal component analysis on the normalized sample covariance matrix.
2) Extract the first principal component as the final predictor, which alone captures more than 50% of the data variability.
3) Estimate a logistic model for downgrade events with the first principal component.

The final functional form for deterioration propensity:

$$Deterioration\ Propensity = f\left(\sum_{i=1}^{5} \beta_i T(x_i)\right)$$

Where $x_1, \ldots, x_5$ are the five EWTK risk metrics: RiskCalc EDF level, Relative EDF level, EDF term structure, EDF change, Relative EDF change; T is feature z-score normalization; f is the logistic function.

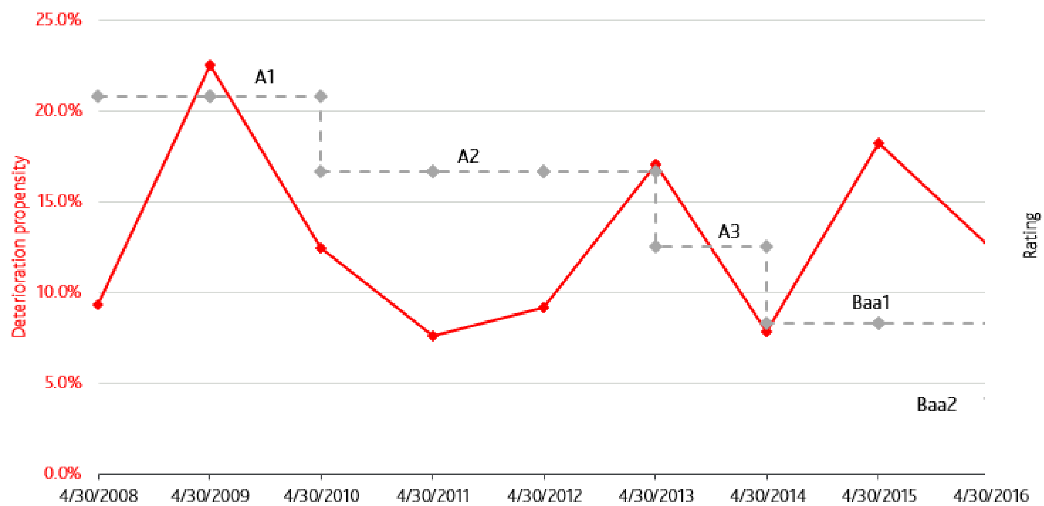
The overall model AR is 23.25%, which is relatively low, due to the lack of powerful predictors such as past rating history and market signals in the model.

[4] Principal component analysis is a commonly used technique for feature extraction, especially useful when dealing with multi-collinearity among raw features. Principal components are the weighted-average of raw features, which capture the most variability of the data and, at the same time, are less correlated. In our case, since EWTK risk metrics are all EDF-related, thus correlated, we first conduct principal component analysis to remedy multi-collinearity.

ii) Case Study

Company X is an Austrian energy producer, downgraded multiple times since 2008 due to distressed financial conditions. The company was first downgraded in 2010, from A1 to A2. We notice that deterioration propensity peaked in 2009, one year prior to the downgrade event. Similarly, deterioration propensity provided an early warning signal before the subsequent downgrade events.

Figure 3 Deterioration propensity as a signal of downgrade events.

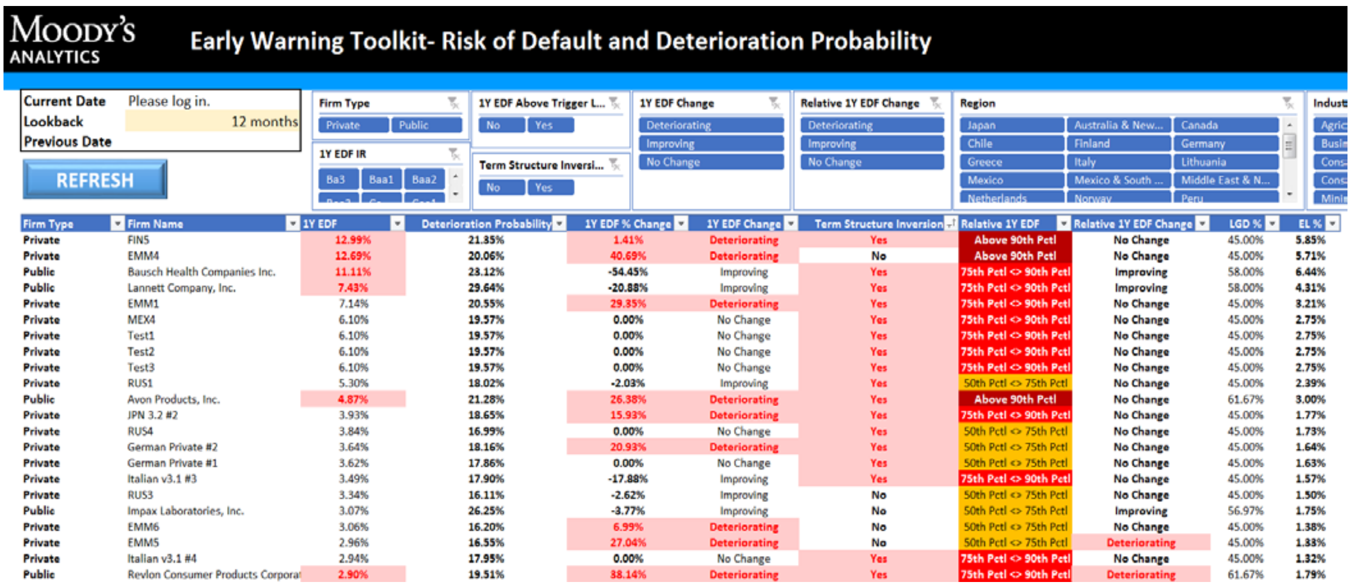


4. Putting It All to Work in Practice

In practice, to help users efficiently analyze exposures in their portfolios and to use the early warning metrics discussed in this paper, we provide an Early Warning Toolkit Excel template that utilizes the Moody's Analytics Excel Add-In. The template offers a way to quickly and easily rank order names in a portfolio based on different risk metrics and to identify which 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 Trigger and Deterioration Propensity signals.

For example, in Figure 4, the one-year EDF level for company "FIN5" is highlighted in red, signaling the firm's EDF level has surpassed its Trigger-EDF level and requires additional attention. The firm's other risk metrics, such as EDF level change, term structure, and relative EDF level also signal a high degree of distress.

Figure 4 Early Warning Toolkit Excel Add-in.



Early Warning Toolkit- Risk of Default and Deterioration Probability

Current Date Please log in.
Lookback 12 months
Previous Date
REFRESH

Firm Type	Firm Name	1Y EDF	Deterioration Probability	1Y EDF % Change	1Y EDF Change	Term Structure Inversion	Relative 1Y EDF	Relative 1Y EDF Change	LGD %	EL %
Private	FIN5	12.99%	21.35%	1.41%	Deteriorating	Yes	Above 90th Pctl	No Change	45.00%	5.85%
Private	EMM4	12.69%	20.06%	40.69%	Deteriorating	No	Above 90th Pctl	No Change	45.00%	5.71%
Public	Bausch Health Companies Inc.	11.11%	23.12%	-54.45%	Improving	Yes	75th Pctl <> 90th Pctl	Improving	58.00%	6.44%
Public	Lannett Company, Inc.	7.43%	29.64%	-20.88%	Improving	Yes	75th Pctl <> 90th Pctl	Improving	58.00%	4.31%
Private	EMM1	7.14%	20.55%	29.35%	Deteriorating	Yes	75th Pctl <> 90th Pctl	No Change	45.00%	3.21%
Private	MEX4	6.10%	19.57%	0.00%	No Change	Yes	75th Pctl <> 90th Pctl	No Change	45.00%	2.75%
Private	Test1	6.10%	19.57%	0.00%	No Change	Yes	75th Pctl <> 90th Pctl	No Change	45.00%	2.75%
Private	Test2	6.10%	19.57%	0.00%	No Change	Yes	75th Pctl <> 90th Pctl	No Change	45.00%	2.75%
Private	Test3	6.10%	19.57%	0.00%	No Change	Yes	75th Pctl <> 90th Pctl	No Change	45.00%	2.75%
Private	RUS1	5.30%	18.02%	-2.03%	Improving	Yes	50th Pctl <> 75th Pctl	No Change	45.00%	2.39%
Public	Avon Products, Inc.	4.87%	21.28%	26.38%	Deteriorating	Yes	Above 90th Pctl	No Change	61.67%	3.00%
Private	JPN 3.2 #2	3.93%	18.65%	15.93%	Deteriorating	Yes	75th Pctl <> 90th Pctl	No Change	45.00%	1.77%
Private	RUS4	3.84%	16.99%	0.00%	No Change	Yes	50th Pctl <> 75th Pctl	No Change	45.00%	1.73%
Private	German Private #2	3.64%	18.16%	20.93%	Deteriorating	Yes	50th Pctl <> 75th Pctl	No Change	45.00%	1.64%
Private	German Private #1	3.62%	17.86%	0.00%	No Change	Yes	50th Pctl <> 75th Pctl	No Change	45.00%	1.63%
Private	Italian v3.1 #3	3.49%	17.90%	-17.88%	Improving	Yes	75th Pctl <> 90th Pctl	No Change	45.00%	1.57%
Private	RUS3	3.34%	16.11%	-2.62%	Improving	No	50th Pctl <> 75th Pctl	No Change	45.00%	1.50%
Public	Impax Laboratories, Inc.	3.07%	26.25%	-3.77%	Improving	No	50th Pctl <> 75th Pctl	Improving	56.97%	1.75%
Private	EMM6	3.06%	16.20%	6.99%	Deteriorating	No	50th Pctl <> 75th Pctl	No Change	45.00%	1.38%
Private	EMM5	2.96%	16.55%	27.04%	Deteriorating	No	50th Pctl <> 75th Pctl	Deteriorating	45.00%	1.33%
Private	Italian v3.1 #4	2.94%	17.95%	0.00%	No Change	Yes	75th Pctl <> 90th Pctl	No Change	45.00%	1.32%
Public	Revlon Consumer Products Corporat	2.90%	19.51%	38.14%	Deteriorating	Yes	75th Pctl <> 90th Pctl	Deteriorating	61.67%	1.79%

5. Summary

The RiskCalc Early Warning Toolkit Excel Add-in is an easy-to-use, yet comprehensive toolkit that allows users to focus costly and scarce resources on a highly targeted selection of the most at-risk names in their portfolios. The toolkit identifies at-risk names within a private firm portfolio well before default, utilizing a number of different EDF-related risk metrics. It is well-established that EDF level is a reliable reflection of expected default risk. In addition to EDF level, relative-EDF level, EDF term structure, EDF change, and relative-EDF change provide additional information to identify at-risk names. Monitoring and evaluating Trigger-EDF level and deterioration propensity can help enhance the credit monitoring process.

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