

**April 30, 2012**

**By Electronic Mail**

Ms. Jennifer J. Johnson  
Secretary  
Board of Governors of the Federal Reserve System  
20th Street and Constitution Avenue, NW  
Washington, DC 20551

**Re: Enhanced Prudential Standards and Early Remediation Requirements for Covered Companies (Federal Reserve Board Docket No. 1438 and RIN 7100-AD-86)**

Moody's Analytics ("MA") appreciates the opportunity to provide comments to the Federal Reserve System's proposed rule "Enhanced Prudential Standards and Early Remediation Requirements for Covered Companies". Our comments center on the proposed use of Expected Default Frequency (EDF<sup>TM</sup>) metrics for public firms as one of several indicators that could trigger a remediation response. As the producer of EDF metrics, Moody's Analytics has a long history of researching the performance of EDF measures, as well as how they can best be employed by banks, insurance companies, and other entities involved in the credit markets. Experience has shown that Expected Default Frequency metrics are useful tools for early warning and monitoring of credit risk. In this respect, we understand the Board's proposal for including them in the set of market based metrics that may trigger a review. However, as we elaborate below, we caution against using EDF measures as automatic triggers for remediation. It should further be emphasized that early warning and monitoring of risk is best achieved by analyzing a broad set of market based indicators. EDF measures can be an important part of that toolkit, but should not be the only measure considered. In the sections that follow we respond to some of the specific questions posed by the Fed's NPR as they relate to the use of EDF measures in the remediation process. Our responses are intended to clarify certain aspects of EDF measures, as well as provide some thoughts and guidance on their appropriate use.

### **I. Brief Background on Expected Default Frequency (EDF<sup>TM</sup>) metrics**

For the sake of clarity, Moody's Analytics Expected Default Frequency (EDF<sup>TM</sup>) metrics are a suite of default probability measures derived using different types of data:

1. Public firm EDF measures – probabilities of default for firms with publicly traded equity and published financial statements that are derived using an asset value modeling approach. They are delivered via the CreditEdge platform. Two related public EDF models are Through-the-Cycle EDF (TTC EDF) measures and Stressed EDF (S-EDF) measures. TTC EDF metrics

isolate long-run credit risk trends at the entity level, while S-EDF measures are conditioned on different macroeconomic scenarios. They are also produced at the entity level.

2. Credit Default Swap Implied (CDS-I) EDF measures – probabilities of default for firms and sovereigns with traded CDS calculated using a reduced form modeling approach. They are also delivered via the CreditEdge platform.
3. Private firm EDF measures – probabilities of default for middle market private firms using an econometric model that primarily relies on accounting data. They are delivered via the RiskCalc platform.

The NPR proposes using public firm EDF measures in its early remediation proposals, so our discussion focuses on them.

### **I. The Board should include market indicators in the early remediation regime**

Question 85 asks whether the Board should include market indicators in the early remediation regime. We believe this is appropriate for Level 1 remediation. Market signals are inherently forward-looking, efficient at assimilating information in a rapid manner, and encapsulate the collective wisdom of many investors. Their quick reaction to news that can affect the credit outlook for an entity or sector makes them ideal early warning indicators of potential future difficulty. The process described for Level 1 remediation is essentially that used by major financial institutions. That is, market-based warning signals trigger further review that includes in-depth analyses using qualitative and quantitative factors. The analyses initiated by the market-based metrics – and not the market-based metrics alone – underpin the subsequent credit-related decisions about the exposures in question.

Furthermore, we believe that effective monitoring of credit risk is best achieved by including a broad and diverse set of market-based risk signals. Equity, bond, and derivatives markets may and often do have differing views of risk for the same set of firms. These differing views can inform, improve, and clarify observed changes in risk, as well as minimize bias and distortions that may affect particular markets.

### **II. Credit Default Swap implied default probabilities should be considered in the set of market-based triggers**

Question 86 asks if other market-based signals should be considered. We recommend including default probabilities that are derived from credit default swap (CDS) spreads in addition to the default probabilities derived from asset value models (e.g., public firm EDF measures). Although the proposals outlined in the Fed’s NPR includes CDS spreads as early warning signals, credit spreads (either from CDS or bonds) in general can sometimes be crude and misleading proxies of individual credit risk for high credit quality firms.

Credit spreads represent the compensation above the default risk-free rate that investors demand for taking credit risk. For a given entity, the spread drivers most often cited are its probability of default (PD) and expected loss given default (LGD). The product of these two terms is called expected credit loss. If a firm were risk free, its credit spread would be zero; similarly, a firm whose liabilities are guaranteed (no loss in the event of default) would also have a near zero spread. In reality, other risks in addition to PD and LGD affect credit spreads. Broadly speaking, a spread consists of three factors:

$$\text{Credit spread} = (\text{PD} \times \text{LGD}) + \text{Other Risk Premia}$$

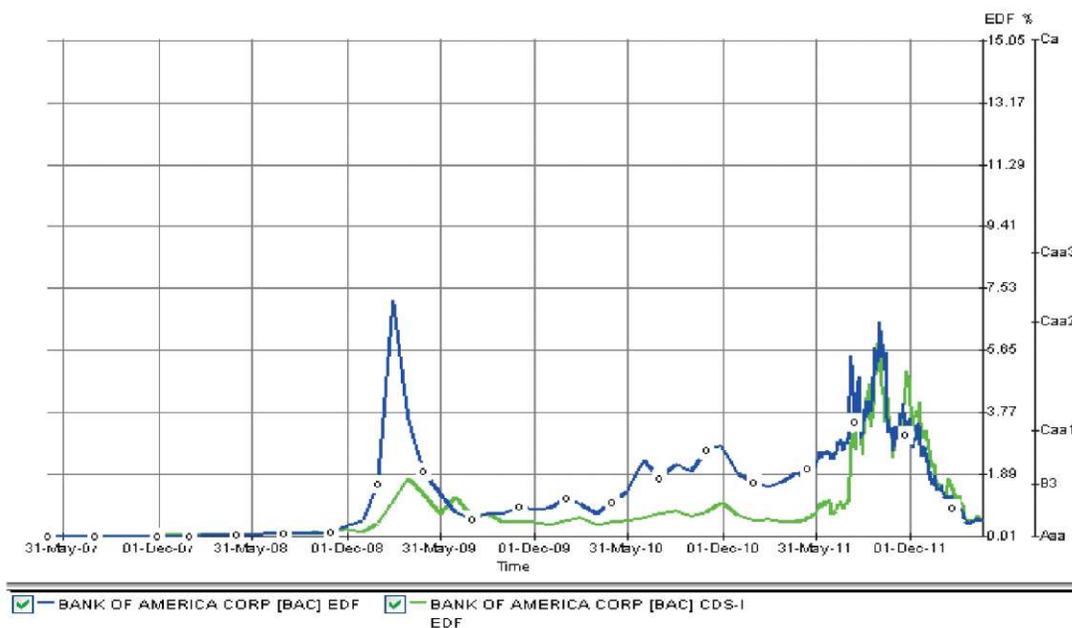
These other risk premia are determined by things such as liquidity, industry and regional risk premia, interest rate risk, and many other market-wide or aggregate level factors not specific to the entity in question. The other risk premia reflected in a spread can be large relative to expected loss (PD x LGD)

for high credit quality firms because the expected default probabilities are often very low. For example, the historical 5-year default rate for Aaa-rated firms is about 4 bp, while currently Aaa CDS spreads are in the neighborhood of 40 bp.

To isolate the individual default risk reflected in CDS spreads, Moody’s Analytics produces CDS-implied EDF (CDS-I EDF) measures. CDS-I EDF measures isolate the default probability embedded in CDS spreads by calibrating LGD and the market risk premium parameters. Hence, CDS-I EDF measures have the same interpretation as public firm EDF measures, and are expressed on the same scale. In the language of the credit risk literature, CDS-I EDF measures are physical default probabilities derived from CDS spreads.

Because CDS spreads often reference senior unsecured obligations, CSD-I EDF measures provide a different view of risk than public firm EDF metrics. This is particularly true for financial institutions. Figure 1 shows the public firm EDF and CDS-implied EDF measures for Bank of America Corp (BAC). During the financial crisis, BAC’s public firm EDF measure was much higher than its CDS-I EDF metric. The gap between the two PD estimates is a consequence of the government’s explicit support for senior lenders, with no commitment to investors further down the capital structure. Public firm EDF metrics measure default *anywhere* in a firm’s capital structure, whereas CDS-implied EDF measures are calibrated to the senior level of risk. Both are relevant for investors and useful for monitoring risk, and no such comparison can accurately be made by using credit spreads alone. Notably, the two measures for BAC have recently converged.

**Figure 1: Public EDF and CDS-Implied EDF Measures for Bank of America Corp.**



### III. Market signals should not serve as automatic triggers for heightened early remediation

Questions 84 and 92 address whether to introduce market triggers for more aggressive early remediation. We do not believe that market-based metrics should potentially lead to specific remediation action or actions, as described for Levels 2, 3, and 4. The principal reason for our position is the volatility of market-based measures. This is noted by the Board (on p.108 of the Notice of Proposed Rulemaking), in particular that market-based triggers can trigger remediation for firms that have no material weaknesses (false positives) and fail to trigger remediation for firms whose financial

condition has deteriorated (false negatives). The result could be to increase the regulatory burden for the Board and for covered companies.

Figure 2 makes this point by illustrating the greater volatility of bond and CDS market signals. Here we compare market metrics to Moody’s Investors Service (MIS) ratings, whose stability over time are well known. We would expect ratings from other major rating agencies behave in a similar fashion. In this example bond and CDS spreads have been mapped to the Moody’s rating scale to produce market-implied ratings. The implied ratings are determined with reference to market-wide benchmarks in the form of median credit spreads for each rating category. The median credit spreads are updated daily, and as such, reflect broad market movements. In this way market-implied ratings have the desirable property of removing market or systemic effects, as you note on p. 110. Despite the adjustment, CDS and bond spread-based metrics remain highly volatile.

**Figure 2: Volatility of Credit Ratings vs. Market-Implied Ratings**

	One-Year Period	
	% with 2-notch changes	% with Ratings Reversals
MIS Ratings	13%	2%
Bond-implied Ratings	81%	86%
CDS-implied Ratings	81%	82%

**IV. Peer comparisons are essential for effective early warning**

Question 94 asks whether and how the Board should use peer comparisons to trigger heightened supervisory review. Our research indicates that peer comparisons are essential for early warning and monitoring using public EDF metrics. Peer group comparisons add additional early warning information beyond the level of EDF alone.

As an illustration, we calculated one-year default rates conditioned on two factors: a firm’s EDF level and the change in its EDF versus the change in the average EDF for its industry sector.<sup>1</sup> For the purposes of this example, industry sector is assumed to be the relevant peer group. In Figure 3 below we show the two-way table of one-year default rates conditioned EDF level and EDF change for a firm versus the change in the average EDF of its industry sector. In order to simplify the presentation of the results, we place both EDF levels (the rows of the table) and relative changes versus industry sector (the columns) into ten equally sized categories (i.e. deciles). Higher firm EDFs correspond to higher numbered categories (i.e., category 1 contains the lowest EDF levels, while category 10 has the highest). Similarly, divergence versus industry sector is increasing in the category number across the columns: 1 represents the best relative EDF change (“outperformance” versus its sector), 10 the worst relative EDF change (“underperformance” versus its sector). The last row shows the one-year default rates for all EDF levels, and the last column shows the one-year default rates for all EDF relative changes versus industry sector peer group.

<sup>1</sup> The change in a firm’s EDF and the change in the average EDF for its industry sector are measured over a one-year horizon. The data covers the 2000-2011 time period for 61 industry sector categories.

We are interested in measuring whether the change in a firm’s EDF change relative to its industry peer group differentiates default risk. First, we can see that EDF level is strongly correlated with realized default rates: reading down the last column we see that default rates rise as the EDF level (measured by the 1-10 category) goes up. The relevant question here is whether default rates exhibit any correlation with EDF change relative to its industry peer group; if there is *no* association, the probabilities on the bottom row should be similar, or randomly ordered.

The bottom row of Figure 3 shows that relative change versus an entity’s industry sector *does* help differentiate default risk beyond the EDF level alone. The data in the last row shows that default rates are increasing with relative performance versus industry sector. The inner cells of the table show that the effect of relative change versus industry sector change holds for levels of EDF where default risk is material.

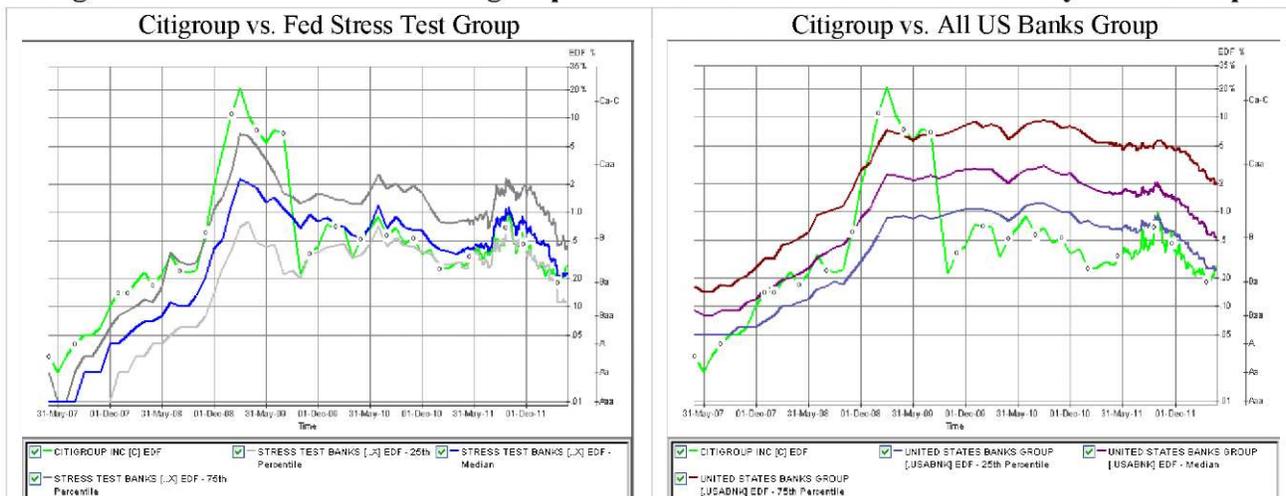
**Figure 3: One-Year Default Rates Conditioned on Firm EDF Level and EDF Change Relative to Industry Peer Group Change**

		EDF Change Relative to Industry Peer Group Change										
		1	2	3	4	5	6	7	8	9	10	ALL
Firm EDF Level	1	0.05%	0.03%	0.02%	0.00%	0.00%	0.01%	0.03%	0.00%	0.00%	0.00%	0.02%
	2	0.10%	0.05%	0.06%	0.06%	0.00%	0.00%	0.02%	0.07%	0.11%	0.27%	0.05%
	3	0.10%	0.06%	0.01%	0.03%	0.01%	0.03%	0.07%	0.06%	0.03%	0.18%	0.05%
	4	0.28%	0.12%	0.17%	0.15%	0.09%	0.10%	0.08%	0.09%	0.17%	0.30%	0.15%
	5	0.32%	0.23%	0.24%	0.32%	0.22%	0.24%	0.21%	0.27%	0.22%	0.46%	0.27%
	6	0.62%	0.44%	0.45%	0.34%	0.44%	0.56%	0.44%	0.72%	0.51%	0.97%	0.55%
	7	0.71%	0.56%	0.66%	0.80%	0.64%	0.72%	0.73%	1.06%	1.18%	1.63%	0.89%
	8	1.01%	1.01%	1.19%	1.25%	1.27%	1.44%	1.58%	1.65%	2.05%	3.10%	1.68%
	9	3.14%	2.22%	4.83%	5.16%	5.25%	4.34%	4.87%	5.75%	6.37%	8.39%	5.60%
	10	6.43%	4.68%	5.76%	7.70%	7.70%	6.96%	7.67%	9.31%	9.99%	13.70%	8.94%
All	0.66%	0.63%	1.08%	1.73%	1.73%	1.83%	2.24%	2.92%	3.13%	5.96%	2.16%	

In order to be effective, peer groups must be carefully chosen in order to minimize false negative signals. A specific example is instructive. In Figure 4 we plot the EDF levels for Citigroup Inc. versus the 25<sup>th</sup> and 75<sup>th</sup> percentiles for a peer group defined two different ways. The first comparison is versus a peer group consisting of 18 of the 19 bank holding companies stress tested by the Fed as part of its Comprehensive Capital Analysis and Review (CCAR).<sup>2</sup> The second peer group is the larger US Banks Group. As the graphs show, Citigroup’s EDF measures shows a much greater degree of underperformance relative to the Fed stress test peer group going into the financial crisis than compared to peer group consisting of all US Banks. Indeed, Citigroup is outside the 75<sup>th</sup> percentile of its peer group for the Fed stress test group as far back as 2007, while it is inside the 25<sup>th</sup> percentile when compared to all US Banks. Depending on the outcome the early warning process was set up to monitor (for example, signal which banks might have needed external financial assistance), the first case might be regarded as true positive, while the second comparison a false negative. We note that both sets of comparisons now basically agree on the improvement in Citigroup’s credit risk (i.e. EDF level) relative to its peers.

<sup>2</sup> Ally Financial Inc. was excluded because it does not have a public EDF measure available.

**Figure 4: EDF Measures for Citigroup vs. Distribution of EDFs for Industry Peer Groups**



We believe that effective peer group analysis should take into consideration:

1. That there are a sufficient number of entities to make comparisons meaningful.
2. That the set of firms is diverse enough (in the risk dimension) to make risk assessments meaningful. The peer group should include firms of a sufficient range of credit quality. Diversity allows for statistical assessment of risk, as well as analogical comparisons (e.g., formerly high quality entity X now has a similar risk profile to risky entity Y).
3. That there are appropriate triggers for review, which may vary from peer group to peer group (in the example in Figure 4 the trigger was the 75<sup>th</sup> percentile of the EDF level), so that false negative signals are minimized.

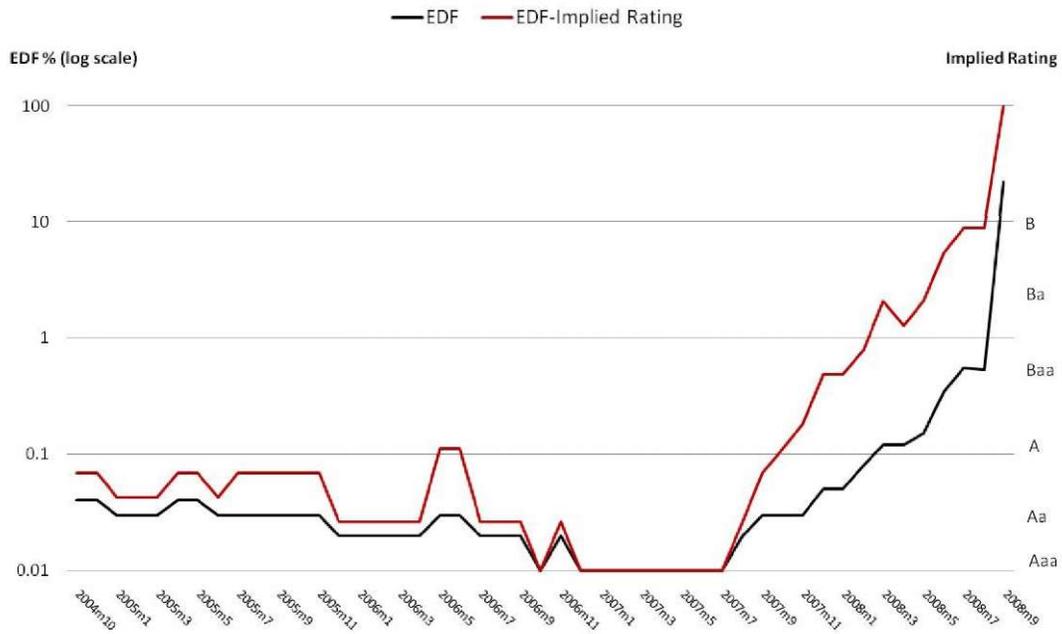
**V. EDF-implied ratings should be consulted in addition to the EDF measure itself**

In Question 95 the Board asks how overall market movements can be accounted for in order to isolate idiosyncratic risk. A straightforward way to remove broad market movements from EDF measures is to use EDF-implied ratings. EDF-implied ratings are calculated by mapping each firm’s EDF level to the rating buck consistent with that level using a grid, which we update monthly. The midpoint of each cell in the grid is the median EDF for that rating class. EDF-implied ratings remove broad market movements in EDF levels. They therefore track broad changes in credit quality. Suppose, for example, a firm has an EDF-implied rating of Aa2. Over some time interval its EDF rises by 10%. As long as the EDF measure for the Aa2 category of firms also rises by 10%, then the implied rating will not change. If the Aa2 group rises by less than 10%, then the firm’s EDF-implied rating will worsen (it has underperformed similarly rated peers); if the Aa2 group’s EDF rises by more than 10%, then the firm’s EDF-implied rating will improve (it has outperformed similarly rated peers). EDF-implied ratings are included in the CreditEdge platform for public firm EDF measures.

In Figure 5 below we show an example of EDF levels and EDF-implied ratings for Lehman Brothers Holdings. As the graph shows, the underperformance of Lehman Brother versus similarly rated firms became greater and greater as the firm approached bankruptcy. In fact, a year before bankruptcy Lehman had an implied rating around the Baa range, which should have called its viability into question,

given its business model. Its EDF level also rose, but was still relatively low in absolute terms very close to the default date.

**Figure 5: EDF levels and EDF-Implied Ratings for Lehman Brothers Holdings**



We thank the Board for the opportunity to provide feedback on its proposal, and would like emphasize that we are available for further discussion on our recommendations.

Sincerely,

Mark E. Almeida  
 President  
 Moody's Analytics

## References

### **Expected Default Frequency (EDF) Models**

#### Modeling Default Risk

<http://www.moodyanalytics.com/~media/Insight/Quantitative-Research/Default-and-Recovery/03-18-12-Modeling-Default-Risk.ashx>

#### CDS-implied EDF<sup>TM</sup> Credit Measures and Fair-value Spreads

<http://www.moodyanalytics.com/~media/Insight/Quantitative-Research/Default-and-Recovery/10-11-03-CDS-Implied-EDF-Credit-Measures-and-Fair-Value-Spreads.ashx>

#### Banks and their EDF Measures Now and Through the Credit Crisis: Too High, Too Low, or Just About Right?

<http://www.moodyanalytics.com/~media/Insight/Quantitative-Research/Default-and-Recovery/10-15-12-Banks-and-Their-EDF-Measures-Now-and-Through-the-Credit-Crisis.ashx>

#### An Empirical Examination of the Power of Equity Returns vs. EDFs<sup>TM</sup> for Corporate Default Prediction

<http://www.moodyanalytics.com/~media/Insight/Quantitative-Research/Default-and-Recovery/10-27-01-Empirical-Examination-of-the-Power-of-Equity>Returns.ashx>

#### Through-the-Cycle EDF<sup>TM</sup> Credit Measures

<http://www.moodyanalytics.com/~media/Insight/Quantitative-Research/Default-and-Recovery/2011/11-01-08-TTC-EDF-Methodology.ashx>

### **Bond, CDS and Equity-Implied Rating Models**

#### Market Implied Ratings Transitions: Performance during the Credit Crisis

[http://v3.moody.com/viewresearchdoc.aspx?docid=PBC\\_125867](http://v3.moody.com/viewresearchdoc.aspx?docid=PBC_125867)

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

[http://v3.moody.com/viewresearchdoc.aspx?docid=PBC\\_106083](http://v3.moody.com/viewresearchdoc.aspx?docid=PBC_106083)

### **Accounting Based Risk Models**

#### Moody's KMV RiskCalc® V3.1 United States

<http://www.moodyanalytics.com/~media/Insight/Quantitative-Research/Default-and-Recovery/04-01-06-RiskCalc-v3-1-US.ashx>

#### Level and Rank Order Validation of RiskCalc v3.1 United States

<http://www.moodyanalytics.com/~media/Insight/Quantitative-Research/Default-and-Recovery/09-02-09-RiskCalc-v3-1-US-LevelValidation.ashx>

#### Bank Failures Past and Present: Validating the RiskCalc V3.1 U.S. Banks Model

<http://www.moodyanalytics.com/~media/Insight/Quantitative-Research/Default-and-Recovery/09-08-10-RiskCalc-V3-1-US-Banks-Validation-Bank-Failures.ashx>