MOODY'S ANALYTICS

MODELING METHODOLOGY

RiskCalc Plus Stress Testing Model (ratio-based approach)

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Abstract

In this paper, we detail a RiskCalc™ Stress Testing Model (ratio-based approach), based upon economic and accounting principles. Our simple, yet fundamental, model assumptions make the framework adaptable to many uses, including: loss forecasting, *pro forma* analysis, stress testing, as a challenger or benchmark model, and for customized scenario analysis.

Our model follows a bottom-up, ratio-based approach, where we fit the model at the individual obligors' financial statements level and then adjust the resulting Financial Statement Only (FSO) Expected Default Frequency (EDF™) credit measure at the credit cycle level. We show how various financial statement inputs behave under different stress scenarios, which, in turn, leads to meaningful variation in EDF credit measures across industries when adjusted for the corresponding credit cycle mode. This methodology is well-suited to being either a primary model or a challenger model within the context of a system-wide stress test. Our model can be used with the Federal Reserve's (Fed's) CCAR scenarios, as well as with other stress scenarios, including user-defined custom scenarios. Validation results show the model performs well both at the intermediate FSO level and at the final Stressed EDF credit measure level. While our methodology has been developed for use with the RiskCalc framework, it can also serve as a blueprint for a bottom-up stress testing framework based upon internal rating models.

This note is an abbreviated overview of our full-length methodology paper. To learn more about this comprehensive version, please contact MA_support@moodys.com.

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1. Overview

Stress testing refers to exercises that enable forward-looking assessment of the potential impact of extreme events (macroeconomic or firm-specific). The initiation of the Financial Stability Assessment Programs by the International Monetary Fund and the World Bank in 1999 brought stress testing to the frontier of financial stability modeling (Drehmann (2008)). Recent events — from financial meltdown in the U.S. to the sovereign debt crisis in Europe — show that stress testing is an integral part of prudent risk management. Using a robust stress testing model, firms can assess their financial vulnerability to extreme events. Macro stress testing, the preferred approach among most central banks in the U.S. and Europe, analyzes the financial stability of a firm under plausible and adverse macroeconomic conditions.[1] The Fed's Comprehensive Capital Analysis and Review (CCAR) reports in 2012 and 2013 provide detailed guidelines for banks and organizations to conduct stress testing under different macroeconomic scenarios.

Stress testing can be classified in various ways: capital vs. liquidity stress testing, sensitivity analysis vs. enterprise-wide stress testing, top-down vs. bottom-up approaches, and many more. Based upon the purpose and scope of the tests, each can be useful in assessing credit, liquidity, and capital risks of the portfolio.

CAPITAL VS. LIQUIDITY STRESS TESTING

Capital stress testing can support an organization's capital planning, helping the firm analyze potential impacts for changes in earnings, losses, reserves, and other effects on capital under various stressful circumstances. This testing includes all the relevant risk types that have the potential to affect capital adequacy, whether directly or indirectly. On the other hand, liquidity stress testing primarily analyzes the liquidity adequacy of an organization. It helps to understand the potential impact of adverse developments that may affect market and asset liquidity, including the freezing up of credit markets and the effect on the firm.[2] The approach we present is more applicable for capital stress testing exercises. Estimating losses requires estimates of the Probability of Default (PD), Loss given Default (LGD), and Exposure at Default (EAD) as well as the loss emergence process. PD is one key element in computing loss estimates, and the EDF credit measure can serve this purpose.

SENSITIVITY ANALYSIS VS. ENTERPRISE-WIDE STRESS TESTING

Sensitivity analysis refers to a firm's assessment of its exposures, activities, and risks when certain variables or parameters are stressed. The main objective is to test the impact of model assumptions on outcomes. But enterprise-wide stress testing refers to assessing the impact of certain, specified scenarios on the organization as a whole with respect to capital and liquidity, in particular. These scenarios for enterprise–wide stress testing can be based upon macroeconomic, market-wide, and/or firm-specific events, as long as they affect the organization as a whole.[3]

TOP-DOWN V.S BOTTOM-UP APPROACHES

Bottom-up stress testing refers to exercises that begin at the individual borrower or individual exposure level and then determine the impact upon their expected losses under a specified adverse business environment. A top-down stress testing approach starts at a higher level of aggregation. The approach could begin with a bank's specific asset class losses (e.g., C&I) or with a specific sector within an asset class (e.g., construction lending), or with a specific asset class and rating classification within an asset class (e.g., Baa-rated construction firms). The top-down approach estimates losses at one level of aggregation and then rolls them up into the enterprise level, and risk exposures are treated as groups with homogeneous characteristics, whereas, in the bottom-up approach, each obligor is treated as a unit of analysis.[4]

[1] A detailed overview of macro stress testing methods can be found in Foglia (2009).

[2, 3] Please refer to *Supervisory Guidance on Stress Testing for Banking Organizations with More than $10B in Total Consolidated Assets* document released by Department of Treasury, Federal Reserve System, and Federal Deposit Insurance Corporation for more details.

[4] Please refer to *Stress Testing Probability of Default for C&I Portfolio: A Granular Approach* for details on the top-down method. The advantage of this approach is that it does not require individual loan level details. The sector and aggregate level probability of default of the portfolio are two key inputs for this model. However, the main disadvantage of such an approach is that the client cannot identify the obligor-level risk drivers, often captured by the financial statements. The crux of the bottom-up approach is that it captures the risk of the individual obligor through the key ratios derived from the financial statements.

Our stress testing model adopts a *fundamental* or *ratio-based approach*, where we model at the individual obligors' financial statement level and then adjust the resulting EDF credit measures for the credit cycle. We see this approach as being more *bottom-up* than many alternatives. We show how different financial statement inputs behave under different stress scenarios and how the impact trickles down to wide variation in EDF credit measures across industries, when adjusted for the credit cycle expansion or recession. Our approach can be applied for both sensitivity analysis and enterprise-wide stress testing. In addition, our approach allows for custom scenarios. User-defined scenarios can consider risks specific to the organization. For example, these could include the default of a key borrower, a natural disaster, or a regional downturn. Using our approach, a bank can analyze the impacts of adverse market and economic conditions on its borrower's cash flows and profitability, and it can also use the forecasted Stressed EDF credit measures to calculate the actual expected loss estimates, required by regulatory authorities. The fundamental analysis can help a bank understand the possible risk drivers that lead to loss estimates. However, this process is challenging, because different obligors have different strategies for adapting to both recessions and expansions, and, consequently, how financial statements respond to a cycle is likely to be firm-specific. The RiskCalc framework is useful for addressing these issues. RiskCalc begins with an assessment of a firm's financial statements and derives an FSO EDF credit measure. It then adjusts for the Credit Cycle Adjustment to produce a Credit Cycle Adjusted (CCA) EDF measure. To the extent that a business downturn leads to poorer financial ratios, a borrower's FSO EDF will increase. An adverse business environment typically results in a negative signal Credit Cycle Adjustment, so the CCA EDF measure will increase as well.

For the above reasons, we build our fundamental approach upon the RiskCalc framework. We construct our model at two levels. First, we fit models on obligor's key financial statement items. We link the key income statement items to the contemporaneous macro variables and use these models to predict the *pro forma* statements. The main assumption here is that the income statement items such as net income, net sales, interest expense, and cost of goods sold are more responsive to business conditions than balance sheet items such as Total Assets or Depreciation, etc. We assume that the macroeconomic signal coming from the income statement finally trickles down to balance sheet items, and, thus, given any stress scenario, the financial statement of an obligor is affected. Further, we predict the credit cycle adjustment factor by linking it to the macro variables and use the CCA factor to adjust the *pro forma* EDF credit measures from the FSO model. It is worth noting that, as many internal rating frameworks for C&I borrowers rely upon financial statement inputs in determining the quantitative component of the PD score, the methods developed in this paper can be borrowed when developing a bottom-up approach based upon internal rating models.

We use the macro variables consistent with those used in the Fed's 2012 and 2013 CCAR exercises. In our methodology, one of the main factors is sector risk, so that different sectors may have different exposures and sensitivities to macro variable shocks. We build sector-specific models to account for such differences. We use a mixture of economic intuition and statistical techniques to select a set of macroeconomic variables. Our final set of macroeconomic variables ensures that the model is robust and will work well within different stress scenarios.

Validation of stress testing model is important as well as challenging. We use a mixture of approaches to validate our framework. First, we compare the actual time series of EDF credit measures to the projected Stressed EDF credit measures computed using the scenario that actually occurred. Using the perfect foresight scenarios, we expect the forecast to be reasonably close to what actually happened. Second, we compare the forecasted EDF measures under the CCAR stress scenarios to what actually happened during the last recession. This method is reasonable, because the forecast periods under CCAR 2012 and CCAR 2013 are comparable to last recession, and, thus, one can expect the forecast Stressed EDF measures to be close to the actual EDF measures for the last recession. Last, we compared the average Stressed EDF measure from our model with the average charge-off implied PDs from the C&I portfolios of all banks as reported by the Federal Reserve Board. We calculate the loss projection and compare it with the CCAR loss projection. Based upon these three validation exercises, our analysis suggests that our fundamental stress testing model works well for different stress scenarios.

1.1 Applications of the RiskCalc Stress Testing Framework

LOSS FORECASTING

Our ratio-based approach can be used for evaluating the capital adequacy of an enterprise under different stress scenarios. Using the Stressed EDF credit measures, a firm can forecast the loss amount due to the adverse impact of external market conditions or user-defined stress scenarios upon earnings, reserves, or other capital measures.

CHALLENGER MODEL OR BENCHMARK MODEL

One of the general principles suggested by the regulatory authorities states "An effective stress testing framework employs multiple conceptually sound stress testing activities and approaches." Our model, based upon fundamental analysis, can serve as a benchmark or challenger model. We base our approach upon sound assumptions, and validation results that show that it is capable of generating credible outcomes under different stress scenarios. Thus, if a bank employs its own method of stress testing,

then it can use our model as an alternative approach for a sanity check. By varying the model design and complexities, it can check whether the outcomes are reliable or not.

CUSTOM SCENARIOS

Our framework supports custom scenarios and different scenarios can be applied to different subsets of the portfolio. Therefore, this framework can be used to consider the impact of a severe business downturn in a specific region. Additionally, users can model a severe increase in interest with our approach.

PRO FORMA ANALYSIS

Our model can also be used for estimating the impact of adverse conditions (market-wide or firm-specific) on the *pro forma* financial statements. Based upon key, simple assumptions, our model generates different *pro forma* financial statements for different stress scenarios. A firm can use these *pro forma* statements and impose additional user-defined assumptions to conduct sensitivity analysis as well. The clarity and simplicity of our stress testing model assumptions make our approach flexible and useful for multiple purposes, as described above.

The remainder of the paper is organized as follows: Section 2 describes the RiskCalc data, the macroeconomic scenarios, and variables. Section 3 discusses the RiskCalc framework.[5] Section 4 describes the stress testing model theory. Section 5 discusses basic model specifications. Section 6 shows validation results. Section 7 discusses additional model features. Section 8 concludes.

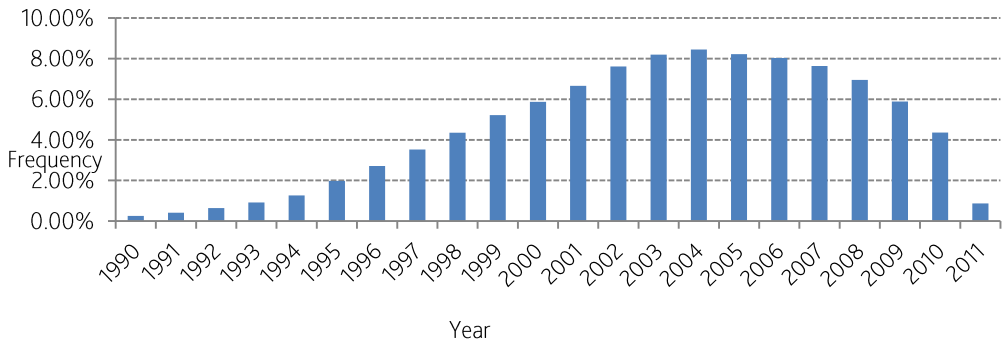
2. Data

2.1 Development Sample

RiskCalc EDF credit measures are based upon the financial statements of middle market exposures collected as part of Moody's Analytics Credit Research Database (CRD) consortium of 15 U.S. financial institutions. These financial statements are the core of the data sets used to develop, calibrate, and validate RiskCalc models.

The base data for this project is composed of these financial statements from the CRD. Specifically, we use the statements and the FSO and CCA EDF credit measures produced by the RiskCalc 4.0 U.S. Model. The data contains financial statements from 1991–2011, covering more than 210,000 firms located in 51 states/districts, and includes more than 1,230,000 statements. The FSO EDF credit measure is annual, whereas the CCA EDF credit measure is monthly. Fourteen major sectors are assigned for all firms in the CRD. They include Agriculture, Business Products, Business Services, Communication, Construction, Consumer Products, Health Care, HiTech, Mining, Services, Trade, Transportation, Utilities, and Unassigned. Firms with missing sectors are grouped under the Unassigned sector in the CRD. We exclude financial institutions, government agencies, real estate companies, and start-up companies from our analysis. Figure 1 presents the distribution of financial statements by year in the development sample.

Figure 1 Distribution of Financial Statements Across Years



[5] For detail, please refer to the RiskCalc US 4.0 model document.

Figure 2 shows the sector coverage of the data. Among the 14 sectors, Trade and Services have the largest coverage of firms and observations and Utilities and Communication contain the smallest number of firms.

Figure 2 Distribution of Financial Statements Across Sectors

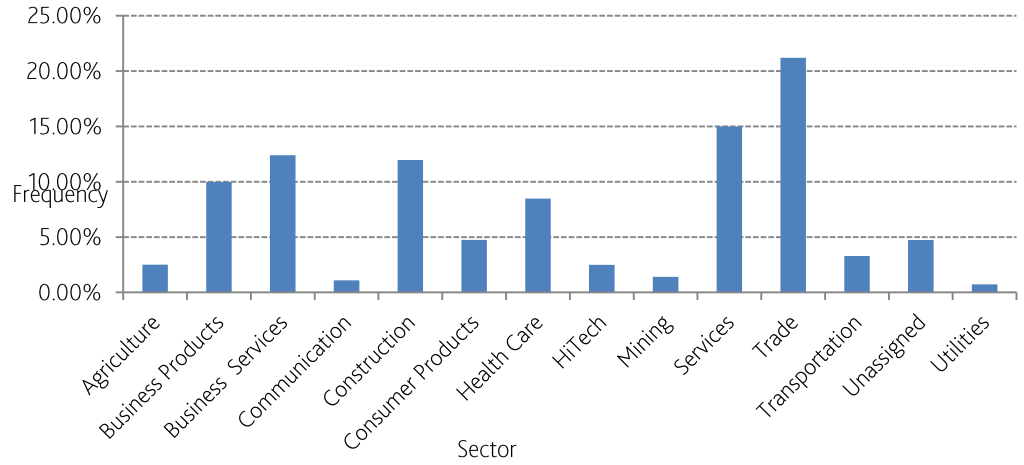
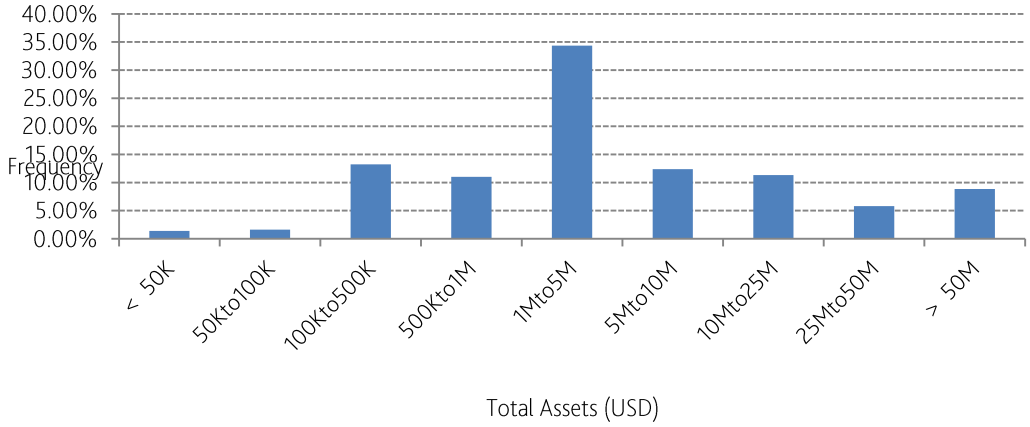


Figure 3 illustrates the size coverage of the underlying data in terms of Total Assets. The group with Total assets 1M to 5M USD has the maximum number of observations. The size coverage shows that the data represents the Small- and Medium-sized businesses, in general.

Figure 3 Distribution of Financial Statements Across Total Assets Groups



2.2 Macroeconomic Scenarios

The main purpose of stress testing is to establish a relationship between macroeconomic variables and the EDF credit measure. Using the model, users can apply the hypothetical stress scenarios via the projected macro variables to stress initial EDF credit measures over the nine quarters. In this subsection, we briefly describe the hypothetical scenarios and highlight their differences in terms of a few key macro variables considered in our model.

According to the Fed's CCAR 2012: Methodology and Results for Stress Scenario Projection document, the Fed incorporated 26 economic variables, including both 14 domestic and 12 international attributes. At a high level, the domestic U.S. variables include:

- Six measures of economic activity and prices
- Four aggregate measures of asset prices or financial conditions
- Four measures of interest rates

The international variables include four regions: Europe, UK, developing Asia, and Japan. For each region, we consider the following attributes:

- GDP
- Inflation
- Exchange rate

The historical data from the Fed's CCAR and MEDC are quite similar, except for a few variables, even though these variables are obtained from the same source. These differences are due to the timing when the data is obtained from the source. The forecast horizon for CCAR 2012 is from Q4 2011–Q4 2014, whereas, that for CCAR 2013 is from Q4 2012–Q4 2015. MEDC updates the data monthly.

We note that the MEDC Scenario S4: Protracted Slump is the most severe stress scenario. Among the CCAR scenarios, the CCAR 2013 Severely Adverse scenario is more stressed than the CCAR 2012 Stress scenario. One thing to note is the difference between variables in CCAR and MEDC. CCAR reports the Dow Jones Index to measure asset prices, whereas MEDC reports the S&P 500 Stock Price Index to measure the same. However the one-year returns of both these series have similar trends. Another key difference is the measure of the volatility of market environment. CCAR reports the CBOE Volatility Index (VIX), whereas MEDC reports the volatility of the S&P 500 Index. These two measures differ in terms of their levels. To be consistent between these two measures, we use historical VIX and S&P volatility to fit a model that can predict VIX for different MEDC scenarios. This detail can be obtained from the authors upon request. Other key variables such as Interest Rates, BBB Corporate yield, and House Price Index are similar, except for their respective differences in forecast horizons over the CCAR and MEDC Scenarios. Table 1 provides the details of these variables.

2.3 Macroeconomic Variables and Transformations

As we are currently focused on stressing a domestic middle market C&I portfolio, we concentrate on domestic macroeconomic variables. Each variable has historical data covering Q1 2001 to Q4 2011. The CCAR 2012 was conducted by the Fed back in November 2011 for loss projections beginning in Q3 2011.

Table 1 DOMESTIC CCAR MACROECONOMIC VARIABLES

Economic Activity and Prices	Real GDP growth
	Nominal GDP growth
	Real disposable income growth
	Nominal disposable income growth
	Unemployment rate
	CPI inflation rate
Interest Rates	3-month Treasury yield
	10-year Treasury yield
	BBB corporate yield
	Mortgage rate
Market Price and Volatility	Dow Jones Total Stock Market Index
	Market Volatility Index (VIX)
Real Estate	House Price Index
	Commercial Real Estate Price Index

The CCAR 2013 uses the same macro variables, but instead of two scenarios, Baseline and Stressed, it now has three: Baseline, Adverse, and Severely Adverse. Beside the original CCAR variables, we also considered additional variables:

» Credit Spread defined as the difference between the Baa Bond Yield and the 10-year Treasury yield. This variable is supposed to capture bond investors' risk premium, which should have strong correlation with firms' future default risk.

» West Texas Intermediate (WTI) oil index is used for some sectors that are highly dependent on oil price.

We include various macroeconomic variables and their transformations in our model to capture the shocks, the innovations, and the lags of impact of these variables.

3. RiskCalc 4.0 U.S. Framework

The RiskCalc 4.0 U.S. model incorporates various components to determine the EDF credit measure. Model inputs include selection of the financial ratios, transforms of those ratios, the inclusion of industry information, and the credit cycle adjustment.

RiskCalc model development involves the following steps:

1. Choose a limited number of financial statement variables for the model from a list of possible variables.
2. Transform the variables into interim probabilities of default using non-parametric techniques.
3. Estimate the weightings of the financial statement variables using a probit model, combined with industry variables.
4. Create a (non-parametric) final transform that converts the probit model score into an actual EDF credit measure.
5. Economic Theory of the Stress Testing Model

4.1 Stress Testing at the FSO Level

As discussed in the prior section, RiskCalc calculates the FSO EDF credit measure of a private firm by weighing information from several financial ratios constructed from their respective financial statements and the firm's industry sector. When the economy falls into a recession, the financial ratios derived from the firms' financial statements worsen, and the corresponding FSO EDF credit measure increases. To capture this relationship between financial statements and macroeconomic variables, we must investigate which of the financial statement items are highly correlated with the economic conditions. Thus, at the FSO level, choosing the appropriate dependent variables from the financial statement is important for creating an effective stress testing model.

4.1.1 Selection of Dependent Variables

The use of financial statement data to link the macroeconomic factors and default probabilities can help in estimating the performance of a bank's exposure separately. We theorize that an adverse business environment causes a firm's revenue to contract along with its variable costs, but the variable costs are likely to contract at a slower rate, thereby causing profits to decline. We also theorize that a firm's interest expense will respond to interest rates, but the impact will take some time, because a portion of the firm's liabilities will have a fixed interest rate.

The financial ratios can be constructed from the balance sheet and/or from the income statement. Balance sheet items such as Assets, Liabilities, Accounts Receivable, Accounts Payable, etc. are difficult to model, as the transmission of the changing macro conditions takes time to impact these variables. For example, if the macroeconomic condition deteriorates, then Total Assets will not be affected until after a certain time lag. Further, the change in a firm's balance sheet depends upon both the firm's income statement and the firm's investment decisions. The latter are difficult to forecast. For this reason, we model the income statement econometrically and then make some simple assumptions regarding how the income statement activity flows through to the balance sheet.

We check whether ratios based on financial statement items are most responsive to key macro variables, such as Real GDP Growth and Unemployment. We run several regressions of each dependent variable onto different combinations of macro variables to analyze whether or not these ratios have a significant impact on the operating profit, and, at the same time, also produce significant stress on the FSO EDF credit measures. We also want to select only those ratios that can capture the inter-linkages between financial statements and macro variables uniformly across sectors.

5.1.2 Assumptions and Scenario Analysis

The idea behind building a stress testing model based upon key financial ratios is to generate a *pro forma* Income Statement for each obligor, which relates the changes in sales and costs to changes in income, which, finally, impacts key balance sheet items such as Cash, Total Assets, Current Liabilities, Total Liabilities, and Retained Earnings.

Users should keep in mind that there are many different ways to arrive at *pro forma* financial statements. We model only one of many options, which we found to generate reasonable stress on the FSO EDF credit measure when macroeconomic conditions worsen.

4.2 Adjusting for the CCA Factor

Stressed EDF credit measures are impacted not only by a company's financials, but also by the general credit cycle in the economy. To capture this effect, we include a proxy for the credit cycle adjustment (CCA) factor. The RiskCalc 4.0 U.S. model uses the Distance-to-Default (DD) calculation from Moody's Analytics Public Firm Model. It extracts default risk signals from the stock market performance of individual firms. The difference between the current average DD in an industry and its historical average forms the industry-level index for the credit cycle adjustment. For stress-testing purposes, we must adjust the stressed FSO EDF credit measures for the corresponding stressed credit cycle as depicted by the hypothetical macroeconomic stress scenarios.

The final stressed EDF is a product of pro forma FSO EDF and the stressed CCA factor, with certain final transform, specifically:

$$\text{Stressed EDF} = F\big((the\ stressed\ CCA\ factor) * \ the\ pro\ forma\ FSO\ EDF\big)$$

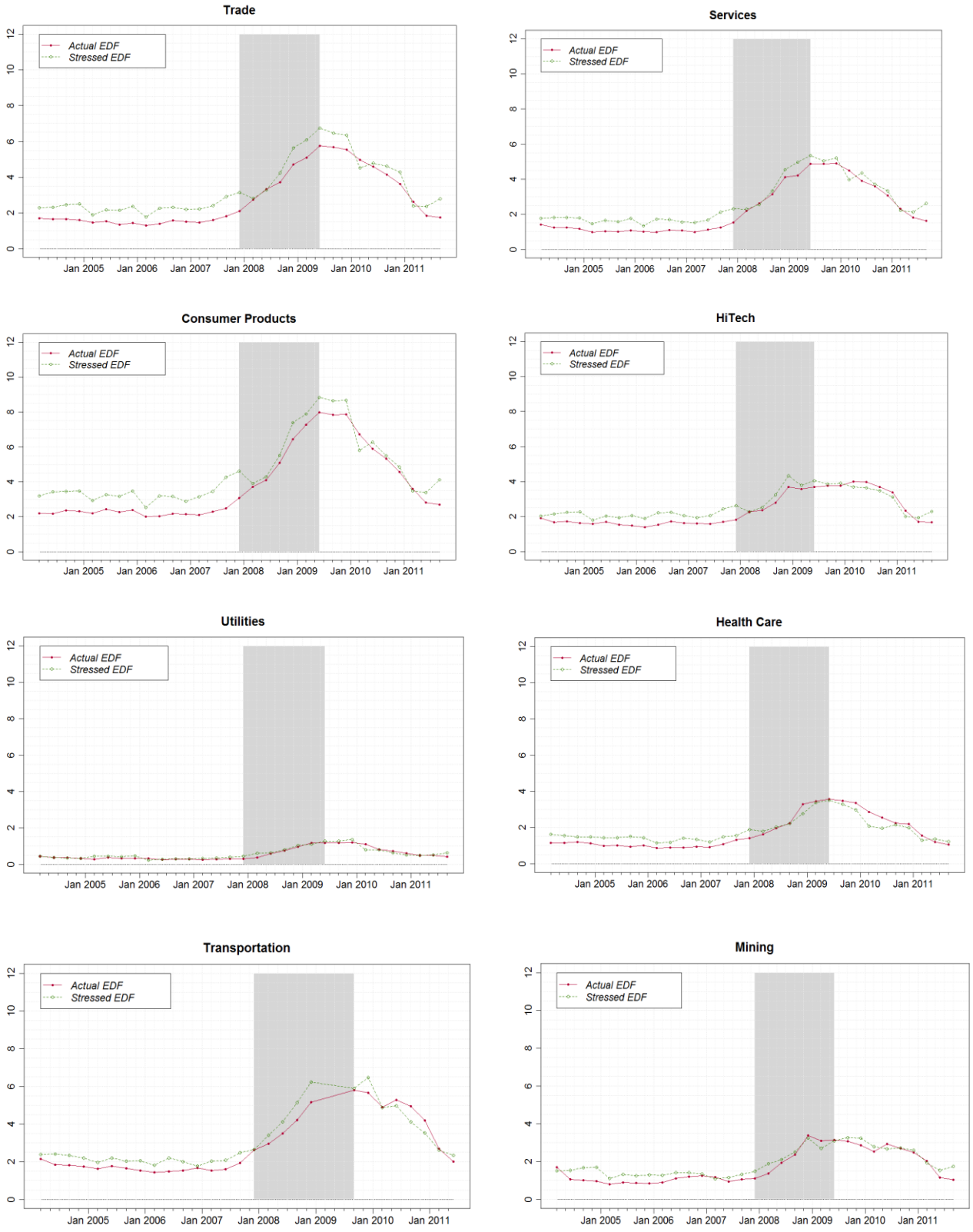
6. Validations

Validation of stress testing models is challenging. We build a stress testing model to understand how an obligor's EDF credit measure behaves if business conditions change. These business conditions are hypothetical, and, thus, the predicted EDF credit measures in these hypothetical scenarios are difficult to validate. Given this challenge, one way to validate the model is to compare the actual CCA EDF credit measure with the predicted Stressed EDF credit measure using the realized macro variables, i.e., the case of perfect foresight. We use the model to generate Stressed EDF through 2011, and then compare it with the actual CCA EDF credit measures for the obligors for which we have financial statements in the CRD.

In this section, we provide validation graphs for a few large sectors. For each year through 2011, we use the obligor's financial statements and the realized macro variables to generate the *pro forma* statements for the consecutive years and the corresponding *pro forma* FSO EDF credit measures as described in Sections 4 and 5. Using the realized macro variables, we also predict the CCA factor for those obligors. Using these two components, we generate the final Stressed EDF credit measures for each obligor. We then average the final Stressed EDF and actual CCA EDF credit measures for these obligors at each time point. For example, we take the financial statements of 2005 for each sector and generate the *pro forma* statements for 2006 for these obligors in each sector by applying the CCAR macroeconomic scenarios. We generate the corresponding *pro forma* EDF credit measures for 2006 and then apply the predicted CCA factor to generate the Stressed EDF credit measures. We compare the average of the Stressed EDF credit measures of 2006 with the realized CCA EDF of 2006 from that sector. We do this exercise on financial statements for each year from 2004–2011 for each sector and compare our model results with the realized EDF credit measures. We present our analysis in Figure 4, where we plot the average CCA EDF and average Stressed EDF credit measure for each time point. We observe the following from the graphs:

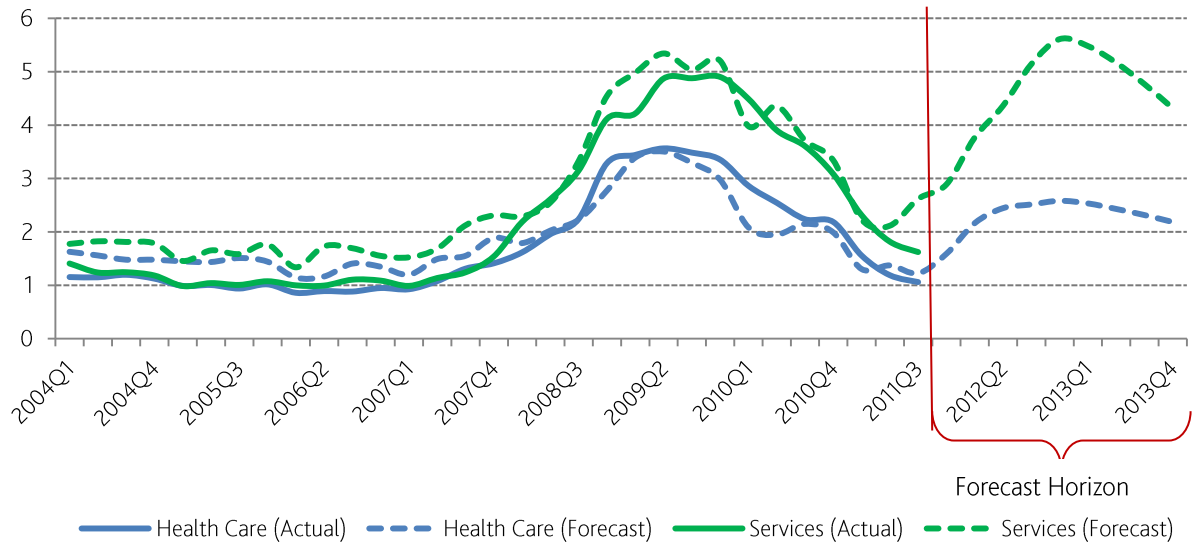
1. Generally, the predicted Stressed EDF credit measure follows the time-series pattern of the actual EDF credit measure.
2. We see that the predicted value matches well with the actual EDF credit measure during the recent crisis (2008).
3. Most of the sectors, such as Trade, Services, HiTech, etc. are highly cyclical, whereas the sectors such as Utilities and Health Care are acyclical, as expected.

Figure 4 Validation Graphs Using Realized Macro Variables



Another way to validate the model for hypothetical scenarios is to compare the predicted Stressed EDF credit measures for a hypothetical stress scenario with the realized actual CCA EDF credit measures. This exercise is meaningful if the macro variables of the underlying hypothetical stress scenario are comparable with the realized macro variables. For example, if the macro variables for 2013–2014 forecast period is comparable with macro variables during the 2008 financial crisis. In that case, one may expect the predicted Stressed EDF credit measures to be at the same level as in 2008. To conduct model validation using this approach, we find that macroeconomic variables under the CCAR 2012 Stress Scenario for 2012–2013 is comparable with the realized macro variables during the 2008 financial crisis. Note that the forecast period for CCAR 2012 begins in Q4 2011. So we use the financial statements from 2010 for two sectors, Services and Health Care, to produce the *pro forma* statements for 2012 and 2013 based on the CCAR 2012 Stress Scenario. Using the *pro forma* EDF credit measures and predicted CCA factors for these nine quarters, Q4 2011 through Q4 2013, under the CCAR 2012 Stress Scenario, we produce the obligor's annualized quarterly Stressed EDF credit measures for each sector. We find that for each sector, the Stressed EDF credit measure peak (average of the Stressed EDFs for obligors for each time point for each sector) over this forecast horizon (after the red line in Figure 5) is close to the realized peak during 2008–2009 for each sector.

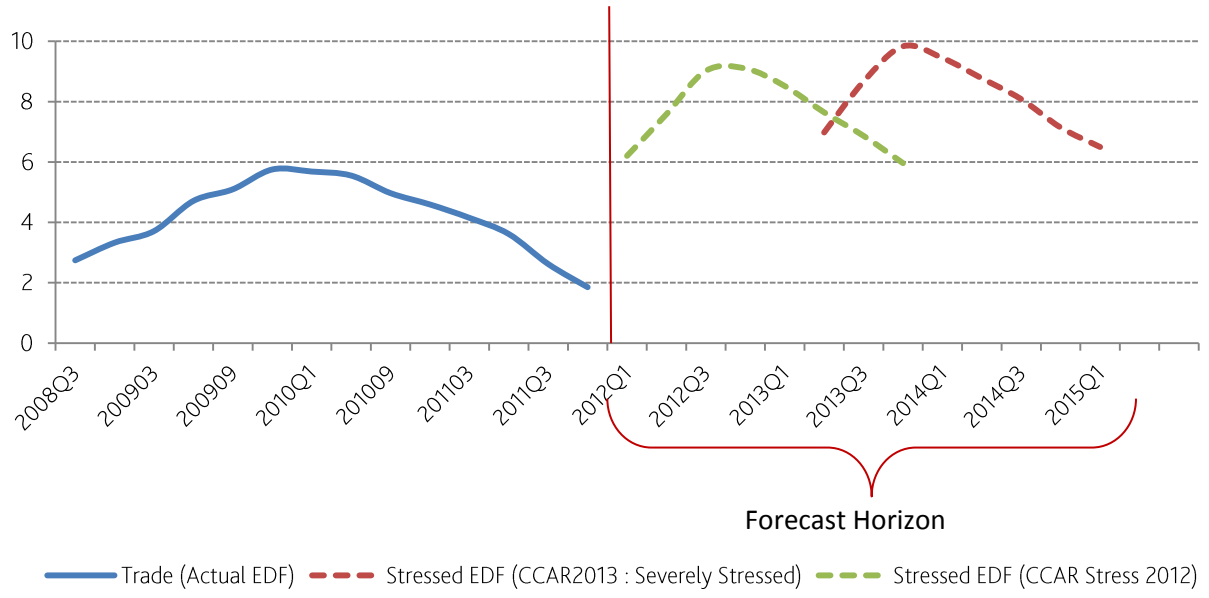
Figure 5 Validation Using CCAR 2012 Stress Scenario



From Figure 5, we find that the peak of the realized CCA EDF (Average) for the Service Sector in 2009 was approximately 5.5%, close to what we observe under the CCAR 2012 Stress Scenario.

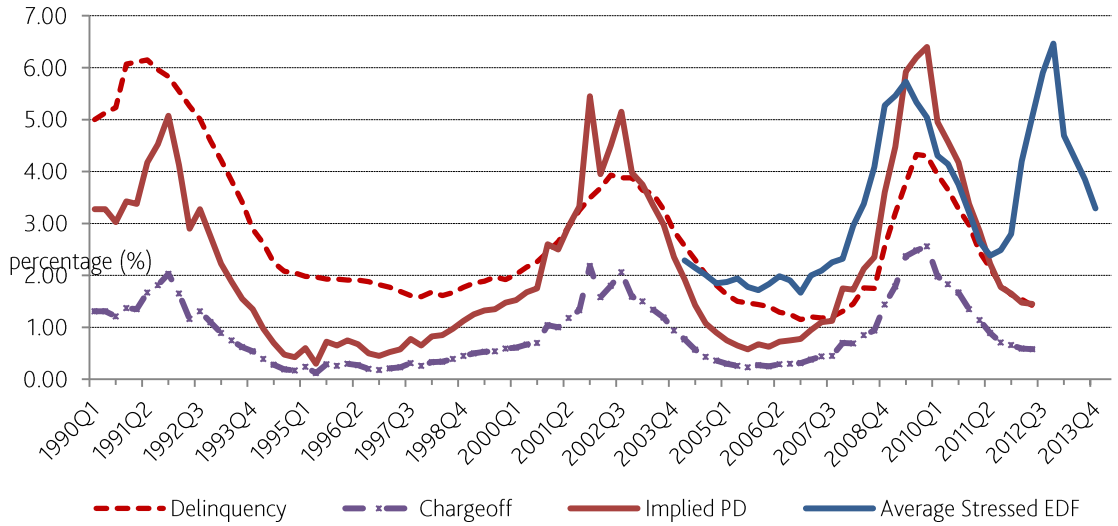
We also compare the Stressed EDF credit measure from the CCAR 2012 Stress Scenario to the CCAR 2013 Severely Adverse Stress Scenario. As mentioned earlier, the macroeconomic variables under the CCAR 2013 Severely Adverse Stress Scenario are comparable with the CCAR 2012 Stress Scenario. However, the forecast period for the CCAR 2012 scenario begins in Q4 2011, whereas the CCAR 2013 scenario begins in Q2 2012. Thus, we expect the Stressed EDF, or at least the peak of the Stressed EDF credit measure, should be comparable between these two scenarios when the same set of financial statements are used. We use obligor financial statements from the Trade Sector in 2009 and generate the *pro forma* statements using the macro variables from the CCAR 2012 Stress Scenario and the CCAR 2013 Severely Adverse Scenario. We apply the forecasted CCA factor under these two scenarios to derive the final Stressed EDF credit measure. The following graph shows that the peaks from these two scenarios are approximately comparable.

Figure 6 Validation Using CCAR 2012 Stress vs. CCAR 2013 Severely Adverse (Sector: Trade)



Finally, we check to see if, on average, the predicted Stressed EDF credit measure (average across all sectors for each quarter) from our model is close to the implied PD from the C&I portfolio of the Federal Reserve Board. Here, the Charge-Offs implied PD (=Charge-Offs/LGD) is computed assuming an LGD of 40%. We find that the peak in 2009 matches well with the implied PD, and the amplitude of the peak of the Stressed EDF credit measures over the forecast horizon in Q4 201 (using the CCAR 2012 Stress Scenario) is comparable with the realized one in 2009. Moreover, using the forecasted average Stressed EDF credit measures from Q4 2011–Q4 2013, we calculate the expected loss at 4.05%, whereas the Fed's calculation for expected loss is 8.2% for this period.

Figure 7 Validation Using the Fed's C&I-Implied PD



Source: Federal Financial Institutions Examination Council (FFIEC) Consolidated Reports of Condition and Income (1985-2000: FFIEC 031 through 034; 2001: FFIEC 031 & 041).

This last validation against external third-party data (using the Fed's data on the C& I portfolio) confirms that our model produces stressed EDF credit measures comparable with the realized EDF credit measures, and the estimates are also reasonable over forecast horizons.

6. Additional Model Features

Additional model functionalities are available. We outline these briefly.

PRO FORMA STATEMENTS

The RiskCalc Stress Testing Model reports the intermediate *pro forma* statements along with the final Stressed EDF credit measures. This functionality can help users understand how the financial statements are affected. Users can analyze the differences between different *pro forma* statements under different macroeconomic scenarios, which enable an in-depth analysis of the *pro forma* statements and quantifies the impact of the different stress scenarios in terms of operating profit, net income, and other key financial ratios.

RELATIVE SENSITIVITY AND RELATIVE CONTRIBUTION

The RiskCalc application provides an analytical tool to gauge the relative impact of each variable as a deviation from the mean of each ratio. Relative sensitivities, also known as sensitivity multiples, exhibit the EDF sensitivity to each model variable at the point of evaluation. It also provides an analytical tool to gauge the relative risk contribution of each variable. The Relative Contribution graph exhibits how each model variable contributes to the EDF value. Like any other RiskCalc model, our stress testing model also reports these two graphs with additional information on each of the variables for *pro forma* one and *pro forma* two statements. Users can conduct a comparative analysis on relative sensitivities and relative contributions on the financial statement and the *pro forma* statements using these graphs.

CUSTOM SCENARIO ANALYSIS

The RiskCalc stress testing framework also allows users to conduct the analysis with user-defined scenarios, including customized stress scenarios specific to the conditions under which a portfolio is likely to be affected the most. Thus, users can treat the pre-defined scenarios, such as the CCAR Stress Scenarios, as a benchmark and then compare the model results with customized scenarios.

7. Conclusion

Our stress testing model, based upon economic and accounting principles, uses a bottom-up approach, where we stress an obligor's financial statements and then adjust the resulting *pro forma* EDF credit measures with the sector-specific CCA factor to obtain final Stressed EDF credit measures. We show how different financial statement inputs behave under different, hypothetical stress scenarios, which, in turn, also affects the wide variation in EDF credit measures across industries, when adjusted for the corresponding credit cycle mode. Validation results at the intermediate and final output stage show that the model performs reasonably well.

It should be emphasized that there are many different ways to build a stress testing framework. However, we base our approach on fundamental analysis, which makes it amenable to many different types of stress testing exercises, e.g., capital stress testing, sensitivity analysis, scenario analysis, and enterprise-wide stress testing. Our simple, yet fundamental, model assumptions make our framework adaptable to many uses. As discussed, the model can be used for loss forecasting, for *pro forma* analysis, as a challenger or benchmark model, and for customized scenario analysis. The model is capable of analyzing different business questions with respect to expected loss calculations and credit risk as required by various regulatory authorities.

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