Complimentary Webinar:
**Integrating Economic Capital, Regulatory Capital and Regulatory Stress Testing in Decision Making**

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Integrating Economic Capital, Regulatory Capital and Regulatory Stress Testing in Decision Making

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Dr. Amnon Levy heads the Portfolio Research Group that is responsible for research and model development for Moody’s Analytics portfolio and balance sheet models.

Dr. Levy holds a B.A. in Economics from the University of California at Berkeley and a Ph.D. in Finance from the Kellogg Graduate School of Management, Northwestern University.

Prior to joining MKMV, Dr. Levy was a visiting assistant professor at the Stern School of Business, New York University, and the Haas School of Business, University of California at Berkeley. He has also taught Corporate Finance at the Kellogg School of Management, Northwestern University and worked at the Board of Governors of the Federal Reserve System. He is currently teaching a course on credit risk at the Haas School of Business MFE program.


His current research interests include modeling credit portfolio risk, integrated models for balance sheet management, as well as liquidity risk.
Agenda

1. Context
2. Current State of Portfolio Management
3. Unified Measures
4. Stress Testing in an Economic Capital Framework
5. Recap
Context
Economic Capital (EC), Regulatory Capital (RegC) and Regulatory Stress Tests (RST)

EC is a measure of economic risk associated with a portfolio

» Accounts for diversification and concentration risks

» Provides insights allowing optimized risk-return profiles, facilitate strategic planning and limit setting, as well as define risk appetite

» Provides a foundation for return-to-risk measures such as RORAC, Sharpe Ratio and Vasicek Ratio to rank instruments

RegC and RST, when binding, results in tangible costs

» Additional capital is needed for new investments

» Changes in portfolio composition can require drastic action
  » Sale of business units
  » Access capital markets at unfavorable terms
**Strategic Questions**

Should RegC replace EC in asset selection?

» With the advent of Basel III, financial institutions face RegC constraints that are increasingly impacting investment plans

» In such environments should an institution replace EC with RegC in RORAC style decision rules?

How should RST enter into decision making?

Is there a need for unified measures?

» RegC and RST are risk measures
  
  » do not account for concentration or diversification effects
  
  » Are associated with tangible costs
  
  » EC does account for diversification, concentration effects, and other economic risks

EC, RegC and RST should all influence decision making
Current State of Credit Portfolio Management
Traditional Measures for Asset Selection

Using traditional measures that accounts for EC but not RegC, The asset should be purchased as long as:

\[ SR_{j,t} = \frac{ES_{j,t}}{RC_{j,t}} \geq \frac{ES_{P,t}}{\sigma_{P,t}}, \text{ or} \]

\[ VR_{j,t} = \frac{ES_{j,t}}{CR_{j,t}} \geq \frac{ES_{P,t}}{CR_{P,t}}, \text{ or} \]

\[ RORAC_{j,t} = \frac{ES_{j,t} + r_{D,t}}{CR_{j,t}} \geq \frac{ES_{P,t} + r_{D,t}}{CR_{P,t}} \]
Motivation Behind Asset Selection Based on Traditional Measures

A financial institution maximizes the utility function of its stakeholders

\[
\text{max } U(C) = E_0 \left[ \sum_t \gamma^t \left( C_t - bC_t^2 \right) \right]
\]

subject to

\[
C_t = \sum_j \left( P_{j,t} + CF_{j,t} \right) N_{i,t-1} - D_{t-1} (1 + r_{D,t}) - \sum_j P_{i,t} N_{i,t} + D_t
\]

\(C\) can be thought of as the dividend policy

Overarching structure is same as that which underpins

- CAPM in portfolio selection
- Black-Scholes style pricing
- NPV capital budgeting using a project’s \(\beta\)
3
Unified Measures
Introducing the Regulatory Capital Constraint

When RegC is binding, an institution faces a tangible cost, which can be considered as an additional constraint in the optimization problem:

$$\max \quad U(C) = E_0 \left[ \sum_t \gamma^t \left( C_t - bC_t^2 \right) \right]$$

s.t.

$$C_t = \sum_j \left( P_{j,t} + CF_{j,t} \right) N_{i,t-1} - D_{t-1} (1 + r_{D,t}) - \sum_j P_{i,t} N_{i,t} + D_t, \quad \text{and}$$

and

$$\text{Book Equity}_t = \sum_j N_{j,t} - D_t \geq \sum_j N_{j,t} RWC_{j,t}$$
Introducing the Stress Testing Constraint

When binding, an institution faces a tangible cost, which can be considered as an additional constraint in the optimization problem:

$$\max \ U(C) = E_0 \left[ \sum_t \gamma_t \left( C_t - bC_t^2 \right) \right]$$

s.t.

$$C_t = \sum_j \left( P_{j,t} + CF_{j,t} \right) N_{i,t-1} - D_{t-1} (1 + r_{D,t}) - \sum_j P_{i,t} N_{i,t} + D_t, \text{ and}$$

and

$$\text{Equity}_{t \mid \text{stress}} = \sum_j N_{j,t} + N_{\text{Liquid},t \mid \text{stress}} - \sum_j EL_{j,t \mid \text{stress}} N_{j,t} - EL_{\text{Liquid},t \mid \text{stress}} N_{\text{Liquid},t} - D_t \mid \text{stress}$$

$$\geq \sum_j N_{j,t} RWC_{j,t \mid \text{stress}} + N_{\text{Liquid},t \mid \text{stress}} RWC_{\text{Liquid},t \mid \text{stress}}$$
Asset Selection with RegC or RST Constraint

The agent should purchase assets as long as:

\[
\frac{SR_{j.t}}{RC_{j,t}} \geq \frac{ES_{j,t}}{\sigma_p} \geq \frac{ES_{P,t}}{\sigma_p}
\]

where

\[
ES_{j,t} = r_{j,t} - r_{DM} \cdot f_{\text{adjustment}_{j,t}}
\]

Only the numerator is affected by the RegC constraint

RegC-adjusted ES is similar to traditional ES but the cost of debt is multiplied by an adjustment factor.
The impact on ES as a function of RegC varies, in part, because of the role of price in the adjustment.
Impact of the RegC Constraint on RORAC

Correlation = 0.874

Impact on RORAC can exceed 50%
Stress testing in an EC framework
Moody’s Analytics RiskFrontier™ framework with our Global Correlation (GCorr™) Macro model

- Draws of borrower specific credit risk factors
- 1-RSQ
- Draws of asset returns (credit quality changes)
- PD, LGD, EAD, Credit Migration
- Credit portfolio loss distribution on a horizon

- Draws of systematic credit risk factors $\phi_{CR1}, \phi_{CR2}, \ldots$
- Correlations of GCorr systematic factors and standard normal macroeconomic factors ($\phi_{MV}$):
- $\Sigma$
- Mapping between $\phi_{MV}$ and macroeconomic variables (MV)
- Scenario for macroeconomic variables (MV) → conditional loss distribution.

EL given a macroeconomic shock
Range of losses given a macroeconomic shock

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What is the impact of an oil price drop on a credit portfolio loss distribution?

A large credit portfolio of homogenous exposures to the U.S. “Oil, Gas, and Coal Expl/Prod” industry

» Input parameters: PD=1%, RSQ=20%, LGD=100%, EAD=1.

Conditional distribution of $\phi_{US,Oil}$ given $\phi_{\Delta \text{OilPrice}}$

Conditional loss distribution, given $\phi_{\Delta \text{OilPrice}}$
What is the impact of an **oil price drop** on a credit portfolio loss distribution?

A large credit portfolio of homogenous exposures to the U.S. “Oil, Gas, and Coal Expl/Prod” industry

» Input parameters: PD=1%, RSQ=20%, LGD=100%, EAD=1.

Conditional distribution of $\phi_{US,Oil}$ given $\phi_{\Delta OilPrice}$

Conditional loss distribution, given $\phi_{\Delta OilPrice}$

Oil Price drops by 2 standard deviations

Conditional distr. Mean=-0.82 Std=0.91

Unconditional distr.

E[\[L|\phi_{\Delta OilPrice}\]] = 2.3%

Unconditional distr.

E[L]=1%

Conditional expected loss:

$$E[L|\phi_{\Delta OilPrice}] = N\left(\frac{N^{-1}(P\Phi)-RSQ}{\sqrt{1-\rho RSQ}}\phi_{\Delta OilPrice}\right)$$

**Terminology:** conditional expected loss, given a macroeconomic scenario, will be also called **stressed expected loss.**
Two ways of using the GCorr Macro model within the RiskFrontier framework:

**Analytical method**
- Calculating stressed expected loss using formulas, which can be evaluated analytically, without a Monte Carlo simulation.
  - The formulas are based on the GCorr Macro model.
- The formulas account only for losses due to defaults, not due to deteriorating credit quality of counterparties.
- The method is simpler and the calculation faster than in the case of the simulation approach.
- The method allows for a CCAR-style analysis.

**Simulation approach**
- Running the Monte Carlo simulation in RiskFrontier with the GCorr Macro model.
- Using the Monte Carlo simulation output for various analyses of credit portfolio losses.
- In addition to calculation of the stressed expected loss, the method allows for:
  - further insights into relationships between losses and macroeconomic variables.
  - determining the full conditional loss distribution.
  - reverse stress testing.
- Accounting not only for defaults, but also for losses due to credit quality deterioration.
- The method takes advantage of the RiskFrontier capability to value various credit risk exposures.
Running RiskFrontier, including the simulation, with the GCorr Macro model

Inputs

Expanded covariance matrix

\[
\begin{array}{c|c|c}
 & \phi_{MV} & \\
\hline
r_C \text{ and } r_I & GCorr \text{ Matrix} & \\
\hline
\phi_{MV} & & \\
\end{array}
\]

Mapping between standard normal macroeconomic factors \( \phi_{MV} \) and macroeconomic variables \( MV \).

RiskFrontier
Monte Carlo simulation engine

Output of Monte Carlo simulation

<table>
<thead>
<tr>
<th>Trial</th>
<th>Simulated macroeconomic factors</th>
<th>Simulated GCorr systematic credit risk factors</th>
<th>Portfolio Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( \phi_{MV1}, \phi_{MV2}, \ldots )</td>
<td>( \phi_1, \phi_2, \ldots )</td>
<td>( L_{Trial 1} )</td>
</tr>
<tr>
<td>2</td>
<td>( \phi_{MV1}, \phi_{MV2}, \ldots )</td>
<td>( \phi_1, \phi_2, \ldots )</td>
<td>( L_{Trial 2} )</td>
</tr>
<tr>
<td>\ldots</td>
<td>\ldots</td>
<td>\ldots</td>
<td>\ldots</td>
</tr>
</tbody>
</table>

Conversion to observable macroeconomic variables \( MV_1, MV_2, \ldots \) using mappings

Output

Analysis of relationships between portfolio losses and macroeconomic variables across trials

Losses can account for credit quality deterioration.
How do correlations vary across U.S. industries?

» Box plots characterizing distribution of correlations between the 61 U.S. custom indexes and select macroeconomic variables

Patterns resulting from a strong interest rate component in asset returns, attributable to financial leverage
How credit portfolio losses depend on various macroeconomic variables…

» IACPM portfolio – 3000 reference entities distributed across 7 developed countries and 60 industries.

» Running simulation engine, which generates draws of systematic factors as well as macroeconomic standard normal shocks ($\phi_{MV}$).
  - Each trial → credit portfolio loss and a macroeconomic shock.

» Example: impact of two macroeconomic variables on the portfolio

Conversion to observable stock market returns using a mapping

Losses more strongly associated with macroeconomic shocks $\phi_{\Delta S&P500}$ than $\phi_{\Delta OilPrice}$. 

Conditional expected loss given the macroeconomic standard normal shock $\phi_{\Delta S&P500}$. 

One trial – portfolio loss versus a draw of the macroeconomic standard normal shock $\phi_{\Delta S&P500}$. 

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CCAR: stressed expected losses over multiple periods in the future

Stressed expected losses over future periods:

\[ \text{PD}^{\text{Scenario}}_{k,1} \times \text{LGD}^{\text{Scenario}}_{k,1} = \text{EL}^{\text{Scenario}}_{k,1} \]

\[ \text{PD}^{\text{Scenario}}_{k,2} \times \text{LGD}^{\text{Scenario}}_{k,2} = \text{EL}^{\text{Scenario}}_{k,2} \]

\[ \text{PD}^{\text{Scenario}}_{k,3} \times \text{LGD}^{\text{Scenario}}_{k,3} = \text{EL}^{\text{Scenario}}_{k,3} \]

\[ \text{PD}^{\text{Scenario}}_{k,4} \times \text{LGD}^{\text{Scenario}}_{k,4} = \text{EL}^{\text{Scenario}}_{k,4} \]

Stressed Expected Loss

Analysis date

Q1

Q2

Q3

Q4
Quarterly FDIC C&I loan performance indicator for all FDIC-insured institutions

Net Charge-offs = \frac{\text{Net Charge-offs}}{\text{Avg Outstanding}} \times 4

Two periods of high losses:
- Dot-com bust recession
- Financial crisis

Time series pattern: Does GCorr Macro imply higher than average losses during recessions and lower than average losses during periods of economic growth?
Historical time series patterns in losses produced by the GCorr Macro model

Variables used in the scenario: unemployment rate, Baa yield, Stock market return, VIX.

9–quarter cumulative stressed expected losses.

Why 9–quarters? → CCAR time horizon

Stressed expected losses increase above the unconditional expected losses during the dot-com recession and the financial crisis.

Why are losses higher during the financial crisis? The financial crisis saw larger quarterly shocks to the stock market and unemployment rate than the dot-com recession.
Recap

» EC, RegC and RST should all influence decision making

» We design decision making variables that bring the three together using a broadly accepted economic framework
  – Accounts for risks related to concentration and diversification
  – Accounts for tangible costs related to RegC and RST

» Link stress testing and EC under a single model
  – Introduce GCorr Macro which unifies credit factors and macroeconomic variables
  – Allows for CCAR/DFAST-style stress testing
  – Provides insights on the extent to which scenarios span portfolio risk
  – Reverse stress testing
  – Risk integration
Thank You

Q&A