Integrating The Macroeconomy Into Consumer Loan Loss Forecasting

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Moody’s Analytics
Integrating The Macroeconomy Into Consumer Loan Loss Forecasting

• Real World Macroeconomic Scenarios: Assessing relevant risks in a forward-looking fashion

• Connecting Macro factors with Risk Parameters: A case study of Retail Stress Testing
  1) Loan level modelling adjusted by economic factors
  2) Portfolio-Vintage models
  3) Overall roadmap: An integrated approach
Real World Macro Scenarios: Assessing relevant risks in a forward-looking fashion
Macroeconomic Scenario Generation

- **Large Scale Macro Models, a la Laurence Klein**
  Demand-Supply Systems of Equations.
  Explicit modelling of industries and macro sectors.
  Not connected to economic theory of consumer behaviour and production.

- **VARs and Structural VARs**
  Data driven models, easier to implement and to maintain.
  Not connected to economic theory.
  Hard to use for stress testing purposes, better for short-term forecasting.

- **Dynamic Stochastic General Equilibrium Models (DSGE)**
  Modern macro models with micro foundations.
  Used widely across central banks and think tanks.
  Limited to a small number of key macro series.
Macroeconomic Scenario Analysis

Alternative Macro Scenarios

Baseline: Recovery

S1: Stronger Recovery
1-in-4

S2: Mild Double Dip
1-in-4

S3: Double Dip
1-in-10

S4: Severe Double Dip
1-in-25

S1: "Stronger Recovery"

S2: "Mild Double Dip"

S3: "Double Dip"

S4: "Severe Double Dip"

Forecast

1:4

1:10

1:20

1:25

1:50

Weaker Economy

Healthier Economy
Macroeconomic Scenario Analysis

Alternative Macro Scenarios

Top 5 Downside Risks

1) Japanese Catastrophe
   Baseline: Recovery

2) Oil Price Shock
   1-in-10

3) Emerging Markets Slowdown
   1-in-20

4) Sovereign Shock
   1-in-50

5) US & Global Severe Recession
   1-in-60

Weaker Economy

Healthier Economy

Forecast

1:50 1:25 1:20 1:10 1:4 1:4
GDP Growth

Developed Markets

Emerging Markets

Source: Moody's Analytics
Peak Unemployment Rate

Developed Markets

Emerging Markets

Source: Moody’s Analytics
Connecting Macro factors with Credit Parameters: A case study of Retail Credit
Connecting Macro factors with Credit Parameters:
A case study of Retail Credit
1) Scoring Models
Consider “Twins” in Parallel Universes

» Universe 1 has just experienced a huge boom and is now predicted to fall into recession

» Universe 2 has just emerged from the worst recession in living memory. Growth is now likely

» Both twins have exactly the same credit history, same loans, same utilizations, same payments, same applications, same delinquencies. Hence, the same credit score.

» Who represents the better credit risk for, say, a mortgage kicked off today? Twin 1 or Twin 2?
# Adjusting the Credit Score

<table>
<thead>
<tr>
<th>Phenomenon (ceteris paribus)</th>
<th>Score Adjustment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Better historical economic performance</td>
<td>Down</td>
</tr>
<tr>
<td>Better economic outlook</td>
<td>Up</td>
</tr>
<tr>
<td>Turning point (end of a recession)</td>
<td>Up (a lot)</td>
</tr>
<tr>
<td>Turning point (end of a boom)</td>
<td>Down (a lot)</td>
</tr>
<tr>
<td>Move from depressed to boom area</td>
<td>Up</td>
</tr>
<tr>
<td>Move from boom to depressed area</td>
<td>Down</td>
</tr>
<tr>
<td>Stable economic performance (permanent depression)</td>
<td>No change</td>
</tr>
<tr>
<td>Stable economic performance (permanent boom, let me know when you find it)</td>
<td>No change</td>
</tr>
</tbody>
</table>
Score Adjustment Varies By State and Over Time

Boom/bust states show a very different adjustment pattern

Source: Moody's Analytics
Score Adjustment Varies By State and Over Time

Boom/bust states show a very different adjustment pattern

Source: Moody’s Analytics
K-S Statistics Lifted by Macro Data

Adjusted Series Does Well When Transiting from Bust to Boom

Source: Moody's Analytics
PD Mapping Largely Consistent Thru Time

For this score band, PD “should be” 0.03

Note that for the unadjusted score, nominal PD is only correct during the validation window.

Source: Moody’s Analytics
SUMMARY

» If we retain percentiles from scoring models, we can reshape the distribution to aggregate default forecasts without affecting K-S.

» Aggregate models can better predict future aggregate default behavior.

» Take account of the “piano accordion effect”. Higher credit risk individuals are more acutely affected by recession than low risk folks

» Deriving a score with the same KS but which predicts future aggregate defaults is strictly welfare increasing.

» Many benefits and few costs, if any.

» “Redlining” is only against speculative behavior.
Connecting Macro factors with Credit Parameters: A case study of Retail Credit
2) Vintage Models
Challenges in Loss Forecasting & Stress Testing

**Issue:** Loan level model can miss correlations and feedback effects

» Individual performance depends on other loans

» Difficult to model individuals within a system

Consumer credit models miss the forest for the trees
– Why not model the forest, model the trees and then make sure the tree model agrees with forest projections?
Consumer Credit Stress Testing
Modeling Approach

Performance Metrics:
- Delinquency Rate
- Default Rate
- Loss Rate
- Recoveries
- Prepayment

Lifecycle Component

Vintage-Quality

Exposure to the Business Cycle
Econometric model: System of equation model using panel data regression techniques to account for latent pool quality

\[ \text{Time series performance for a given vintage of loans} = f \]

**Lifecycle component**
- Dynamic evolution of vintages as they mature
- Nonlinear model against “age”

**Vintage-specific quality component**
- Vintage attributes (LTV, asset class/collateral type, geography, etc.) define heterogeneity across cohorts
- Early arrears serve as proxies for underlying vintage quality
- Economic conditions at origination matter
- Econometric technique accounts for time-constant, unobserved effect

**Business cycle exposure component**
- Sensitivity of performance to the evolution of macroeconomic and credit series
Example of Delinquency Model – Vintage Level

![Image of the Delinquency Model](image-url)

The table below shows the coefficient statistics for the Delinquency Model at the vintage level.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Coefficient</th>
<th>SEC</th>
<th>t-Stat</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment</td>
<td>BLS Household Survey: Unemployment Rate, X, SAAR</td>
<td>0.004512</td>
<td>0.0021</td>
<td>3.21</td>
<td>0.0028 to 0.0064</td>
</tr>
<tr>
<td>Disposable</td>
<td>Disposable Personal Income, X, SAAR</td>
<td>0.00034</td>
<td>0.0002</td>
<td>1.66</td>
<td>0.0002 to 0.0004</td>
</tr>
<tr>
<td>HousePrice</td>
<td>Fannie Mae Single-Family Home Price Aggregate Index, X</td>
<td>0.00005</td>
<td>0.0000</td>
<td>0.56</td>
<td>0.0000 to 0.0001</td>
</tr>
<tr>
<td>VehicleSales</td>
<td>Vehicle Sales, X, SAAR</td>
<td>0.00003</td>
<td>0.0000</td>
<td>1.00</td>
<td>0.0000 to 0.0000</td>
</tr>
<tr>
<td>NIPA</td>
<td>BEA NIPA: Personal Consumption Expenditures: Total, X</td>
<td>0.00002</td>
<td>0.0000</td>
<td>1.23</td>
<td>0.0000 to 0.0001</td>
</tr>
<tr>
<td>VehicleSales4</td>
<td>Vehicle Sales, X, SAAR</td>
<td>0.00004</td>
<td>0.0000</td>
<td>0.98</td>
<td>0.0000 to 0.0001</td>
</tr>
<tr>
<td>Sage1</td>
<td>Sage1 Rural Unemployment Rate</td>
<td>0.00035</td>
<td>0.0000</td>
<td>0.98</td>
<td>0.0000 to 0.0001</td>
</tr>
<tr>
<td>Sage2</td>
<td>Sage2 Urban Unemployment Rate</td>
<td>0.00030</td>
<td>0.0000</td>
<td>0.98</td>
<td>0.0000 to 0.0001</td>
</tr>
<tr>
<td>Sage3</td>
<td>Sage3 Rural Unemployment Rate</td>
<td>0.00024</td>
<td>0.0000</td>
<td>0.98</td>
<td>0.0000 to 0.0001</td>
</tr>
<tr>
<td>Sage4</td>
<td>Sage4 Urban Unemployment Rate</td>
<td>0.00021</td>
<td>0.0000</td>
<td>0.98</td>
<td>0.0000 to 0.0001</td>
</tr>
</tbody>
</table>

Note: This table represents a portion of the full Delinquency Model output which includes various economic indicators and their coefficients.
Consumer Credit Stress Testing
Modeling Approach

Total delinquency rate (% of orig. $) against months-in-book
Consumer Credit Stress Testing
Modeling Approach

Lifetime cumulative loss rate (\% of orig. $) and unemployment against pool

- **Cumulative Chargeoffs (Spliced) [Time 2015M12], Baseline Scenario**
- **BLS; Household Survey: Unemployment Rate, \% SA, Baseline Scenario, US**
Consumer Credit Stress Testing
Modeling Approach

Total delinquency rate (% of orig. $) under different economic scenarios

- Baseline Scenario
- s4: Very Pessimistic Scenario
Consumer Credit Stress Testing
Modeling Approach

Cumulative loss rate (% of orig. $) under different economic scenarios

- Baseline Scenario
- s4: Very Pessimistic Scenario
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3) Overall Solution
Conclusion: Need Holistic Approach to Stress Testing

Industry level forecasting and stress testing
  » Only way to capture feedback loops
  » (Arguably) the only way to capture correct economic loadings

Portfolio level forecasting and stress testing
  » Model level of aggressiveness relative to the industry
  » Model firm specific portfolio characteristics and policies

Loan level modeling
  » Scoring and loan level management. Risk layering.
  » Reporting requirements

Model calibration insures consistency of views
Overall Roadmap, an Example

**Loan Level Scoring Model (LLSM)**
Determine, as well as can be imagined, how the economy affects individual level credit risk.
Does not take into account correlation or macro factors like multipliers and feedback loops
Based closely on Client's Gen 1 scorecard with the addition of economic variables both direct and interactive.

**Quantile Gradient Models (QGMs)**
Models how the differences in score percentiles from the LLSM change over time.
Captures and forecasts how the distribution of default twists and stretches through the cycle
Designed to capture the “piano accordion” effect.

**Establish the “Micro” Features of the Distribution**
- Individual level credit risk affected by economic drivers.
- How percentiles of the distribution change over time

**Default Rate Forecasting**
Models the drivers of the observed default rate.
Uses both internal and external drivers, though internal drivers are deliberately downplayed.
Key driver of the adjustment – we want scores to map closely to observed defaults
Default rate forecasts can be converted to equivalent scores and vice versa

**Establish the Key “Macro” Features of the Distribution**
- Where are aggregate defaults likely to go?
- Business is critically sensitive to movement of overall default probability.

**Putting Everything Together**
I: Take forecast of default rate
II: Convert default rate to an implied average score
III: For each decile, apply QGMs to find what the score at each decile “should be”.
IV: Look up corresponding decile for the Gen 1 scorecard for each region.
V: The difference between what the score should be and what the score is represents the score adjustment
VI: Smooth the series and interpolate
VII: Apply the adjustment to the Gen 1 scorecard.
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