Integrating The Macroeconomy Into Consumer Loan Loss Forecasting

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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

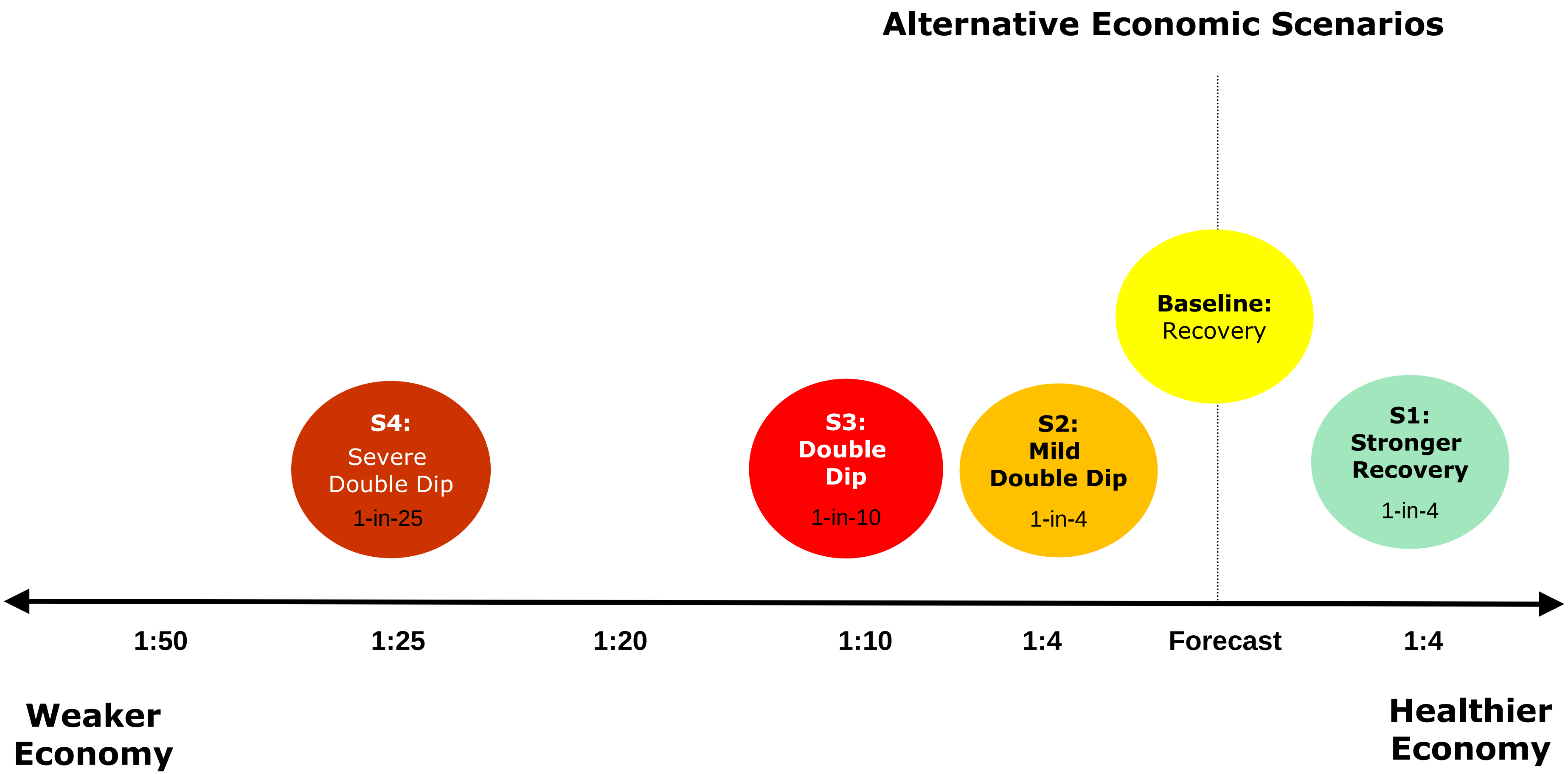
- **Large Scale Macro Models, a la Laurence Klein**
  Demand-Supply Systems of Equations.
  Explicit modelling of industries and macro sectors.
  Not connected to economic theory of consumer behaviour and production.

- **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



Macroeconomic Scenario Analysis

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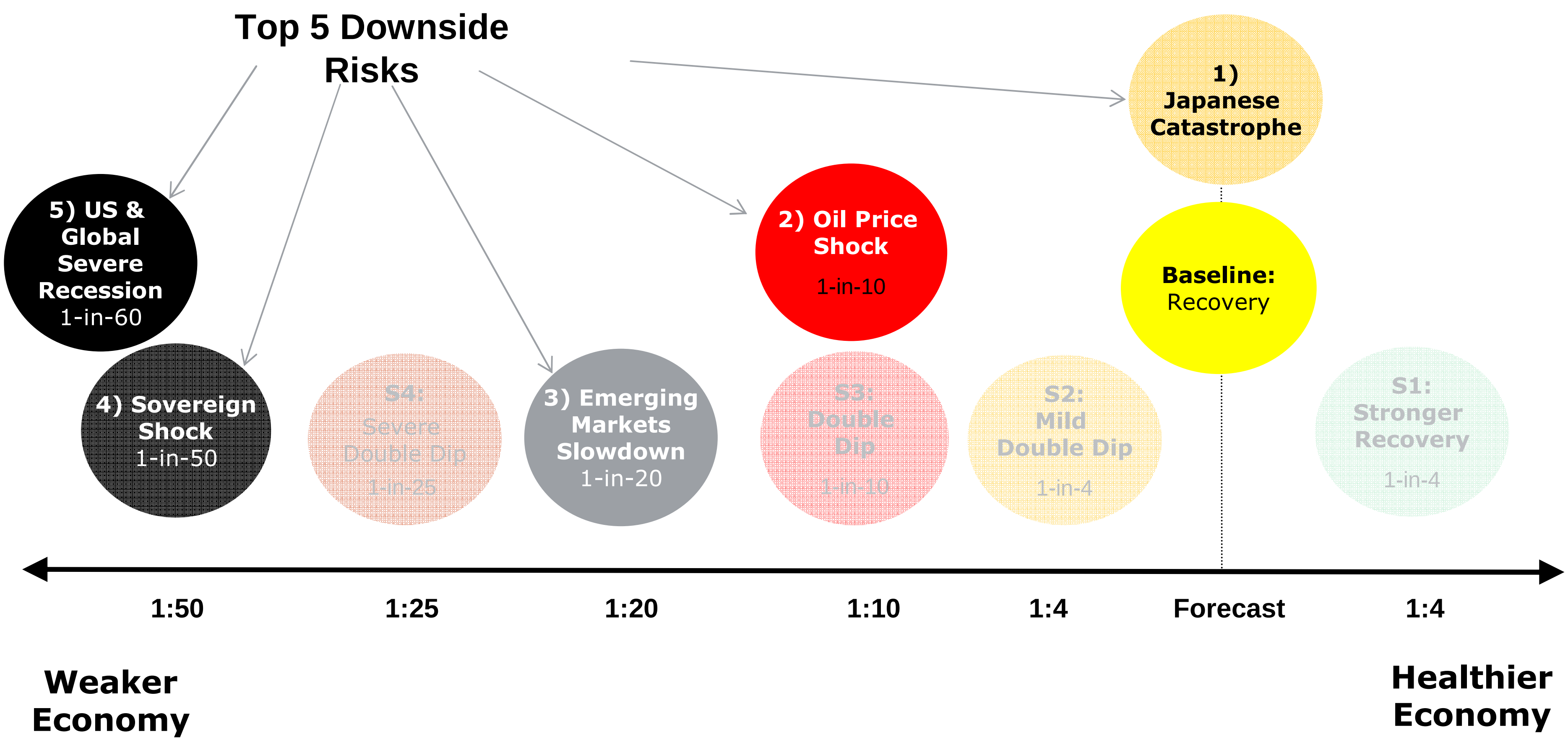
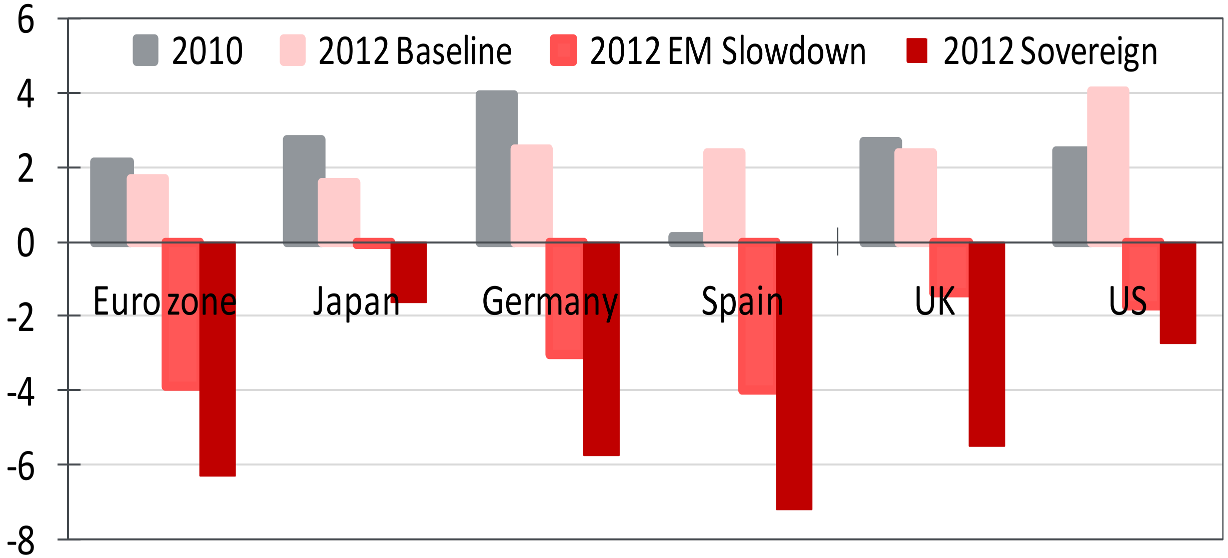


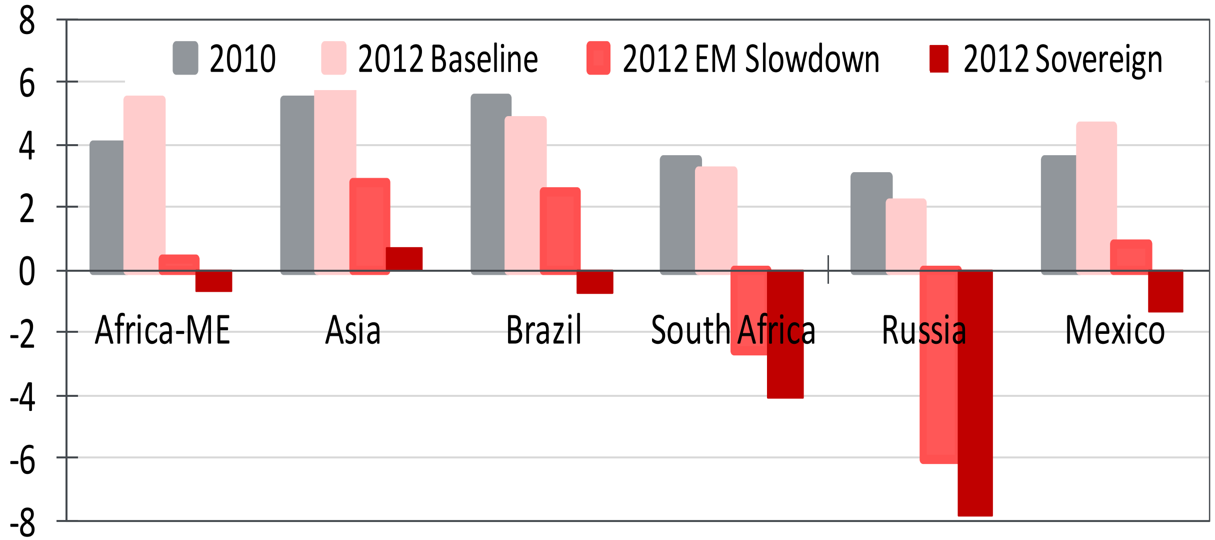
GDP Growth

Developed Markets



Source: Moody's Analytics

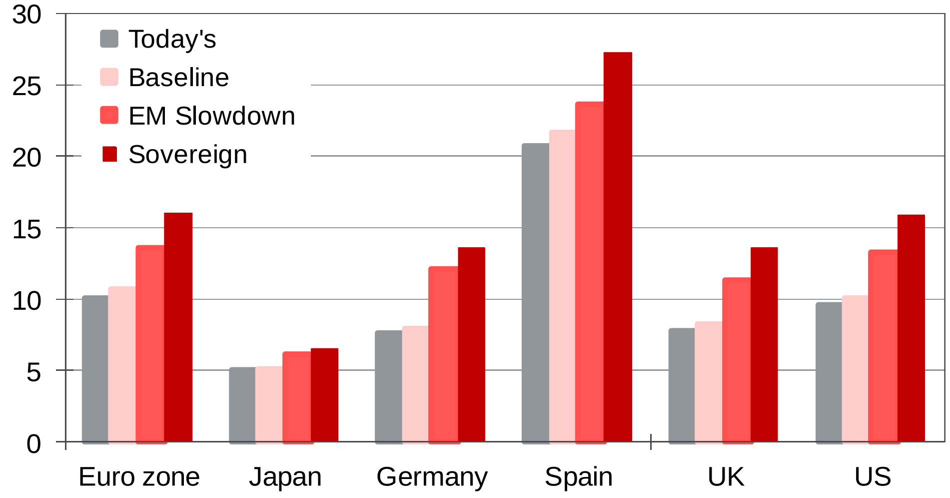
Emerging Markets



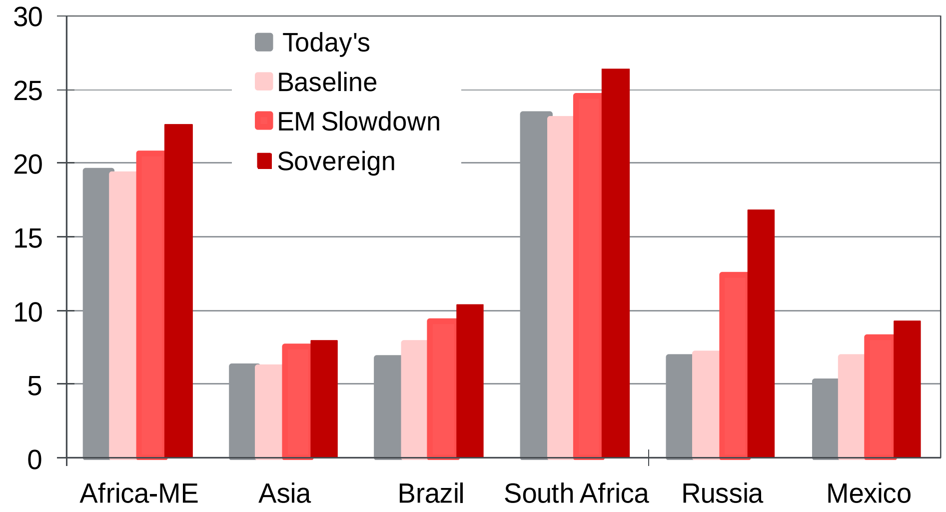
Peak Unemployment Rate

Source: Moody's Analytics

Developed Markets



Emerging Markets



Connecting Macro factors with Credit Parameters:
A case study of Retail Credit

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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.**

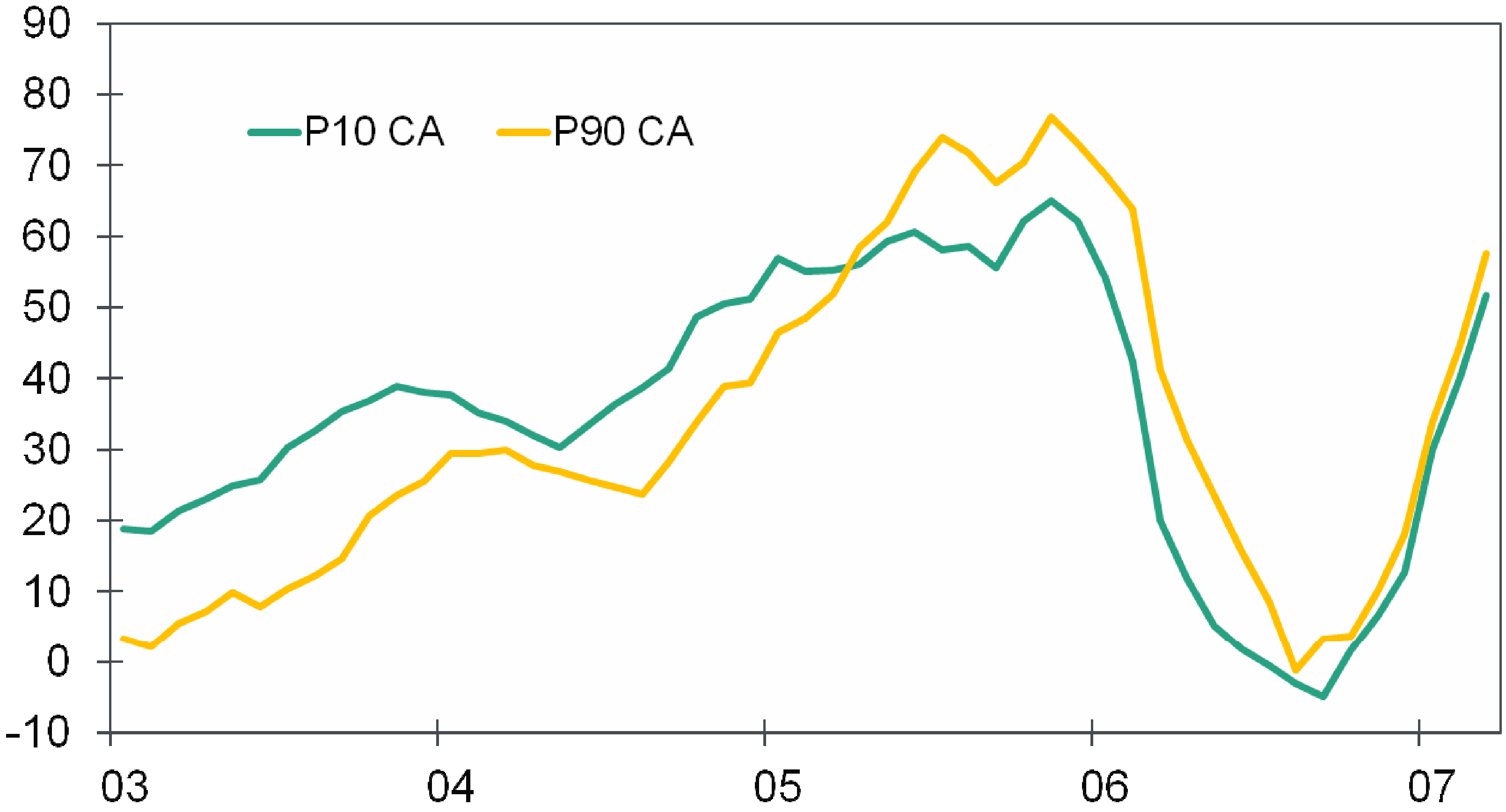
» **Who represents the better credit risk for, say, a mortgage kicked off today? Twin 1 or Twin 2?**

Adjusting the Credit Score

Phenomenon (ceteris paribus)	Score Adjustment
Better historical economic performance	Down
Better economic outlook	Up
Turning point (end of a recession)	Up (a lot)
Turning point (end of a boom)	Down (a lot)
Move from depressed to boom area	Up
Move from boom to depressed area	Down
Stable economic performance (permanent depression)	No change
Stable economic performance (permanent boom, let me know when you find it)	No change

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

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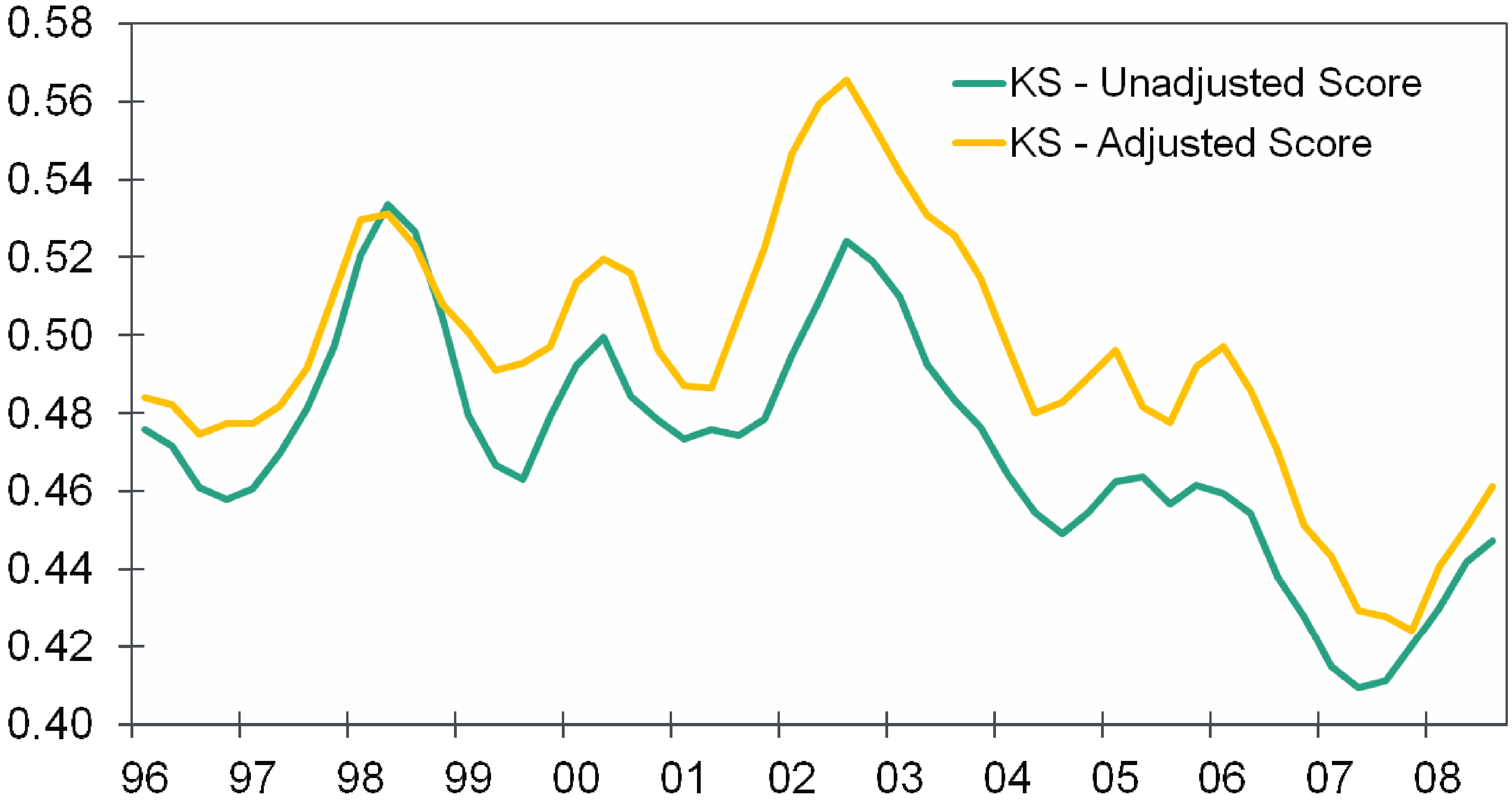
K-S Statistics Lifted by Macro Data

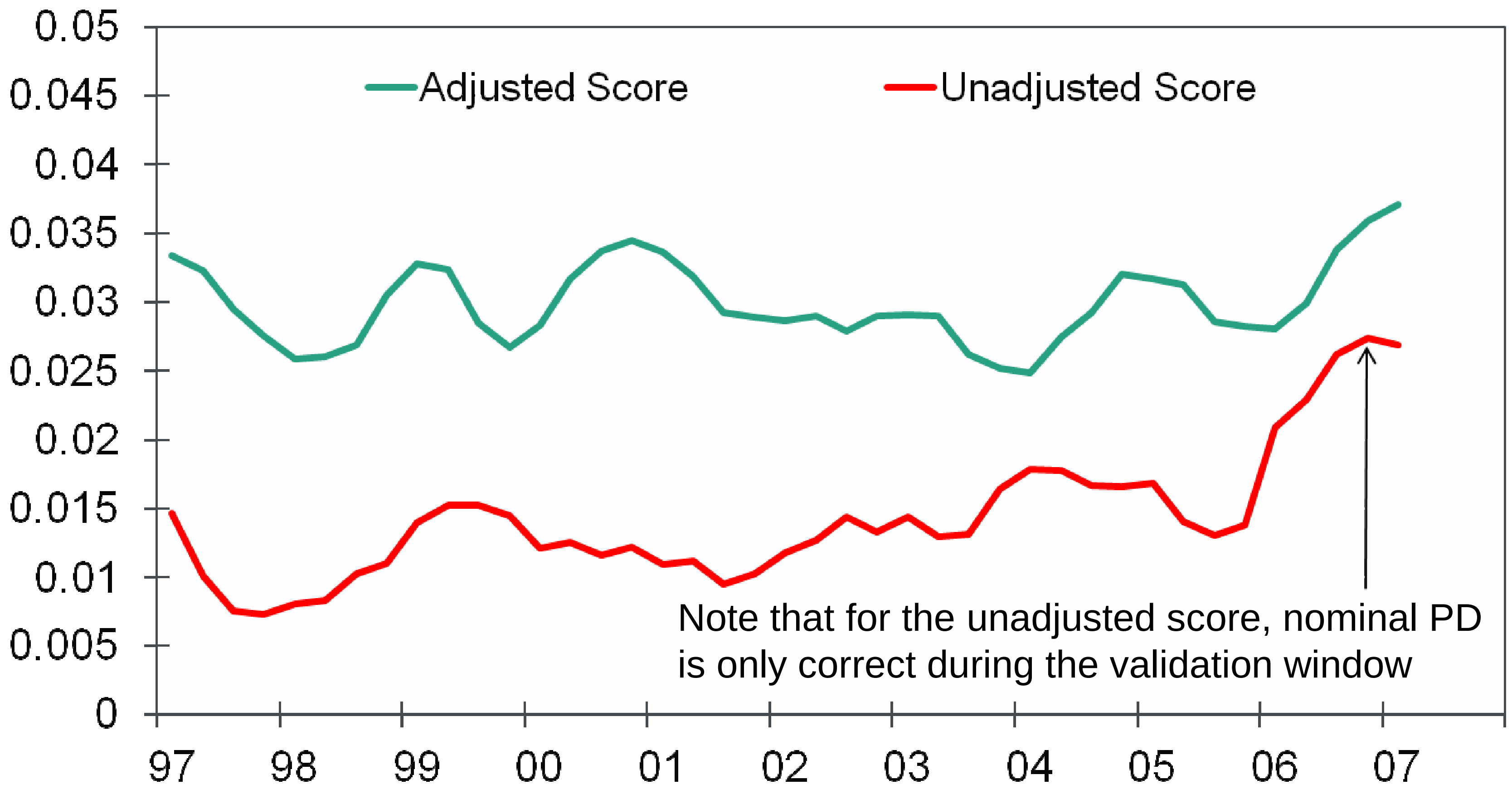
Adjusted Series Does Well When Transiting from Bust to Boom



Source: Moody's Analytics

PD Mapping Largely Consistent Thru Time

For this score band, PD “should be” 0.03



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.

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2) Vintage Models

Challenges in Loss Forecasting & Stress Testing

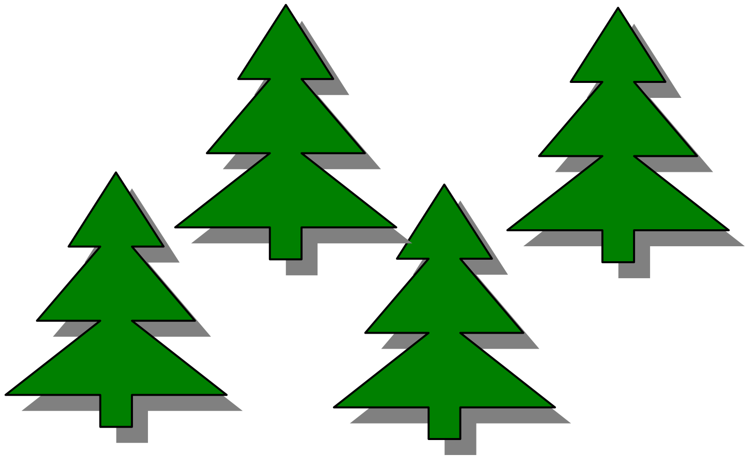
Issue: Loan level model can miss correlations and feedback effects

» 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?



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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

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

Coefficient Statistic

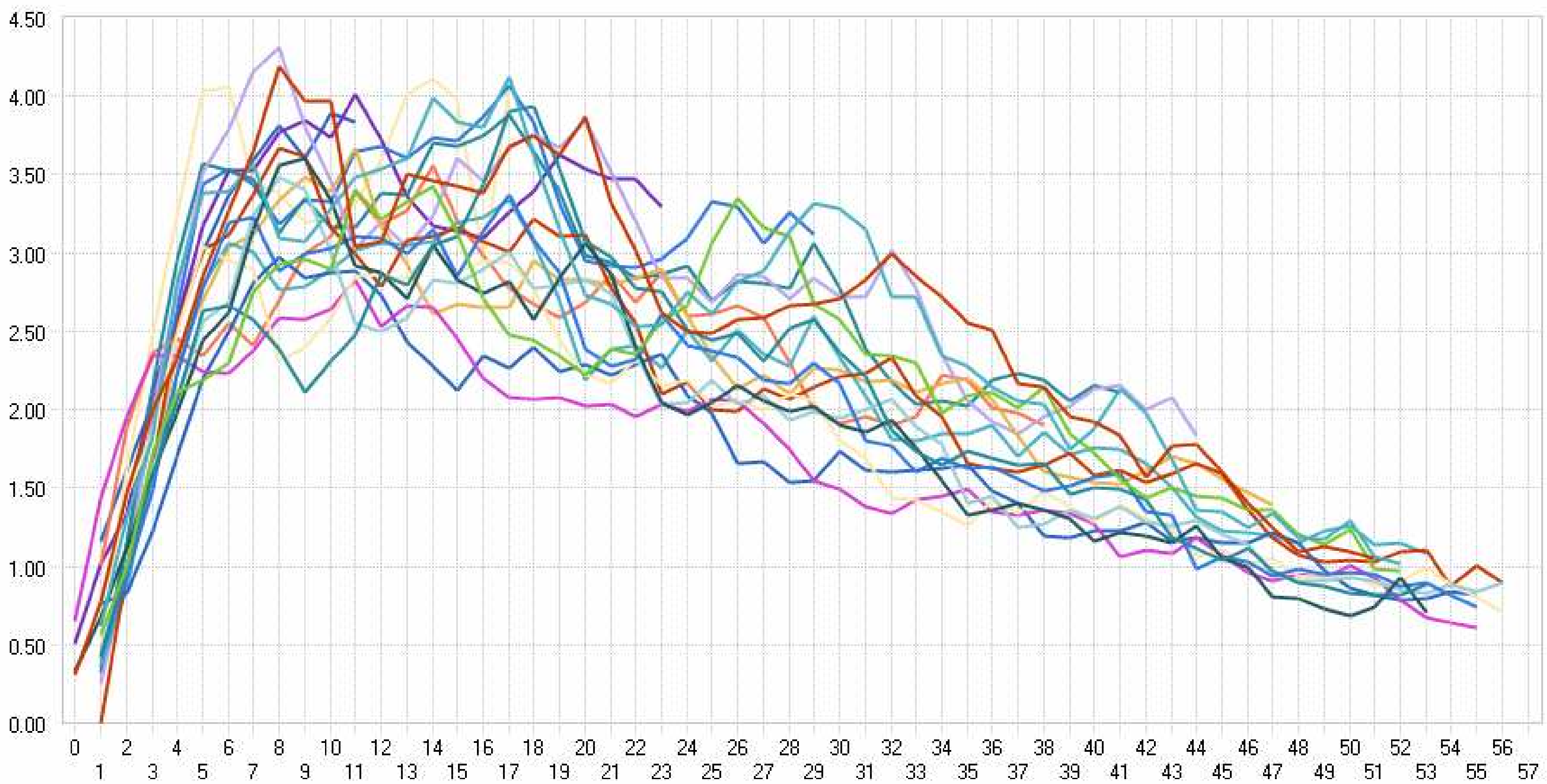
Variable	Description	Coefficient	SEC	tStat	95% Confidence Interval
txxlbr3	BLS; Household Survery: Unemployment Rate, %, SA	0.165880	0.026120	6.350580	0.114684 to 0.217076
tyyxxrdispy	Disposable Personal Income, Bil. $, SAAR	-0.034744	0.004087	-8.500932	-0.042755 to -0.026734
tyyxxcshp3	Fiserv; Case-Shiller Single-Family Home Price Aggregate Index, ...	-0.008715	0.000873	-9.988199	-0.010425 to -0.007005
tyyxxasales3	Vehicle Sales, Mil, SAAR	-0.004130	0.000921	-4.484397	-0.005935 to -0.002325
vxxlbr	BLS; Household Survery: Unemployment Rate, %, SA	-0.095581	0.013357	-7.155754	-0.121761 to -0.069401
vyyxxrcons	BEA: NIPA: Personal Consumption Expenditures - Total, Bil. $, S...	0.035755	0.008307	4.304111	0.019473 to 0.052037
vyyxxasales4	Vehicle Sales, Mil, SAAR	0.002509	0.001213	2.068313	0.000131 to 0.004887
Sage1_p_totalorig_lbr	SAge1 Unemployment Rate	-0.026653	0.003758	-7.092630	-0.034018 to -0.019287
Sage2_p_totalorig_lbr	SAge2 Unemployment Rate	0.383870	0.051199	7.497657	0.283521 to 0.484219
Sage3_p_totalorig_lbr	SAge3 Unemployment Rate	-0.492466	0.066217	-7.437109	-0.622252 to -0.362680
_SAge1	Maturation Component 1	0.294045	0.019099	15.395932	0.256611 to 0.331479
_SAge2	Maturation Component 2	-3.665037	0.259690	-14.113101	-4.174030 to -3.156044
_SAge3	Maturation Component 3	4.617952	0.335942	13.746282	3.959506 to 5.276398
_Const	Constant	-0.395118	0.141115	-2.799979	-0.671703 to -0.118533
_VSeasQ2	Vintage Seasonal Factor Q2	0.094009	0.017640	5.329220	0.059434 to 0.128585
_VSeasQ3	Vintage Seasonal Factor Q3	0.147603	0.017085	8.639090	0.114115 to 0.181090
_VSeasQ4	Vintage Seasonal Factor Q4	0.013962	0.019099	0.731024	-0.023473 to 0.051397
_TSeasFeb	Time Seasonal Factor Feb	-0.068672	0.027120	-2.532160	-0.121826 to -0.015517
_TSeasMar	Time Seasonal Factor Mar	-0.165097	0.027175	-6.075373	-0.218359 to -0.111834
_TSeasApr	Time Seasonal Factor Apr	-0.227246	0.027211	-8.351226	-0.280580 to -0.173913
_TSeasMay	Time Seasonal Factor May	-0.254408	0.026912	-9.453455	-0.307155 to -0.201661
_TSeasJun	Time Seasonal Factor Jun	-0.178540	0.026991	-6.614742	-0.231443 to -0.125637
_TSeasJul	Time Seasonal Factor Jul	-0.157061	0.026943	-5.829370	-0.209869 to -0.104253
_TSeasAug	Time Seasonal Factor Aug	-0.176209	0.026661	-6.609148	-0.228465 to -0.123952
_TSeasSep	Time Seasonal Factor Sep	-0.085688	0.026831	-3.193641	-0.138276 to -0.033100
_TSeasOct	Time Seasonal Factor Oct	-0.070348	0.026918	-2.613459	-0.123107 to -0.017590

Consumer Credit Stress Testing

Modeling Approach

Lifecycle Component

Total delinquency rate (% of orig. $) against months-in-book

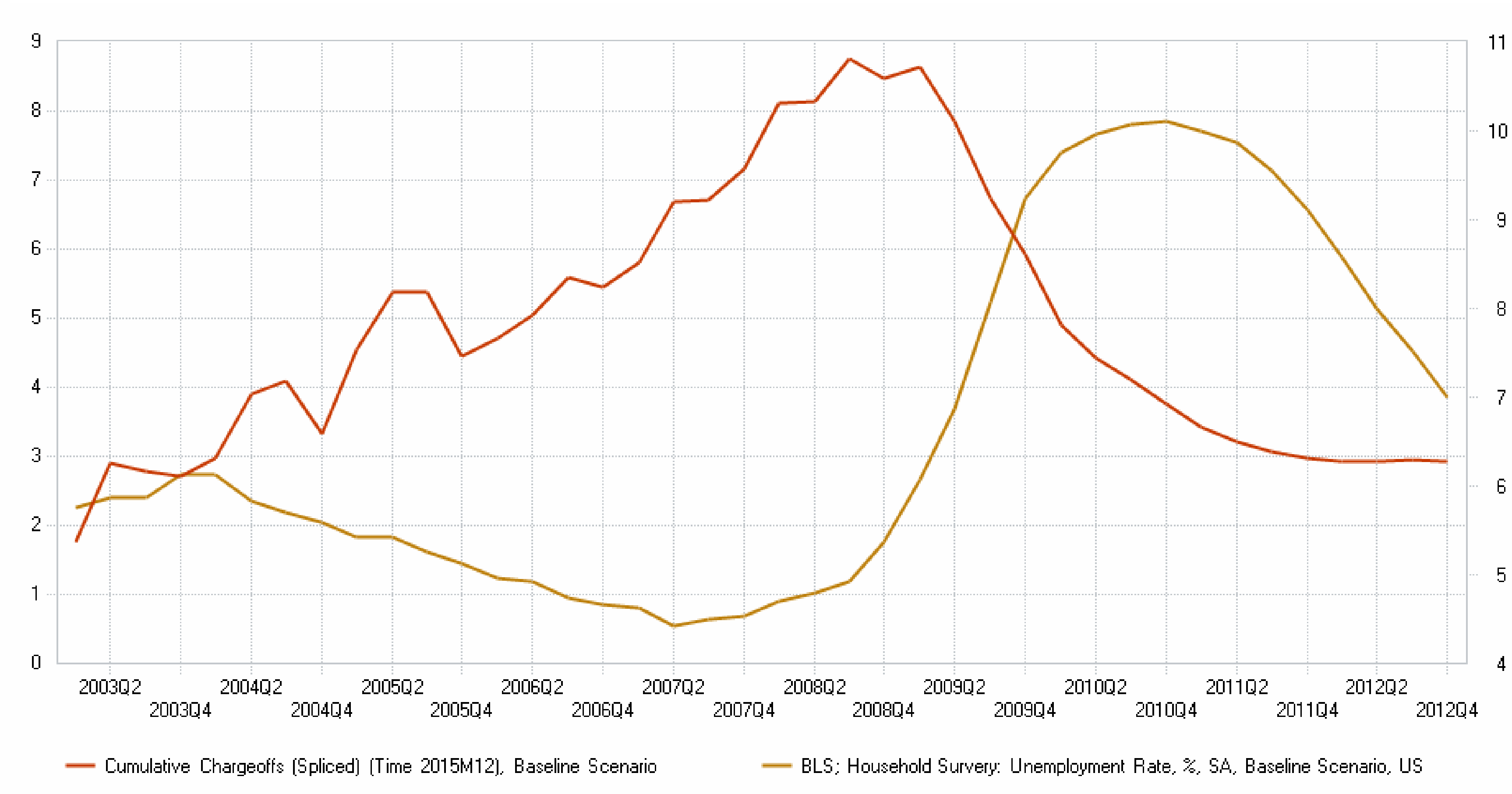


Consumer Credit Stress Testing

Modeling Approach

Vintage-Quality

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

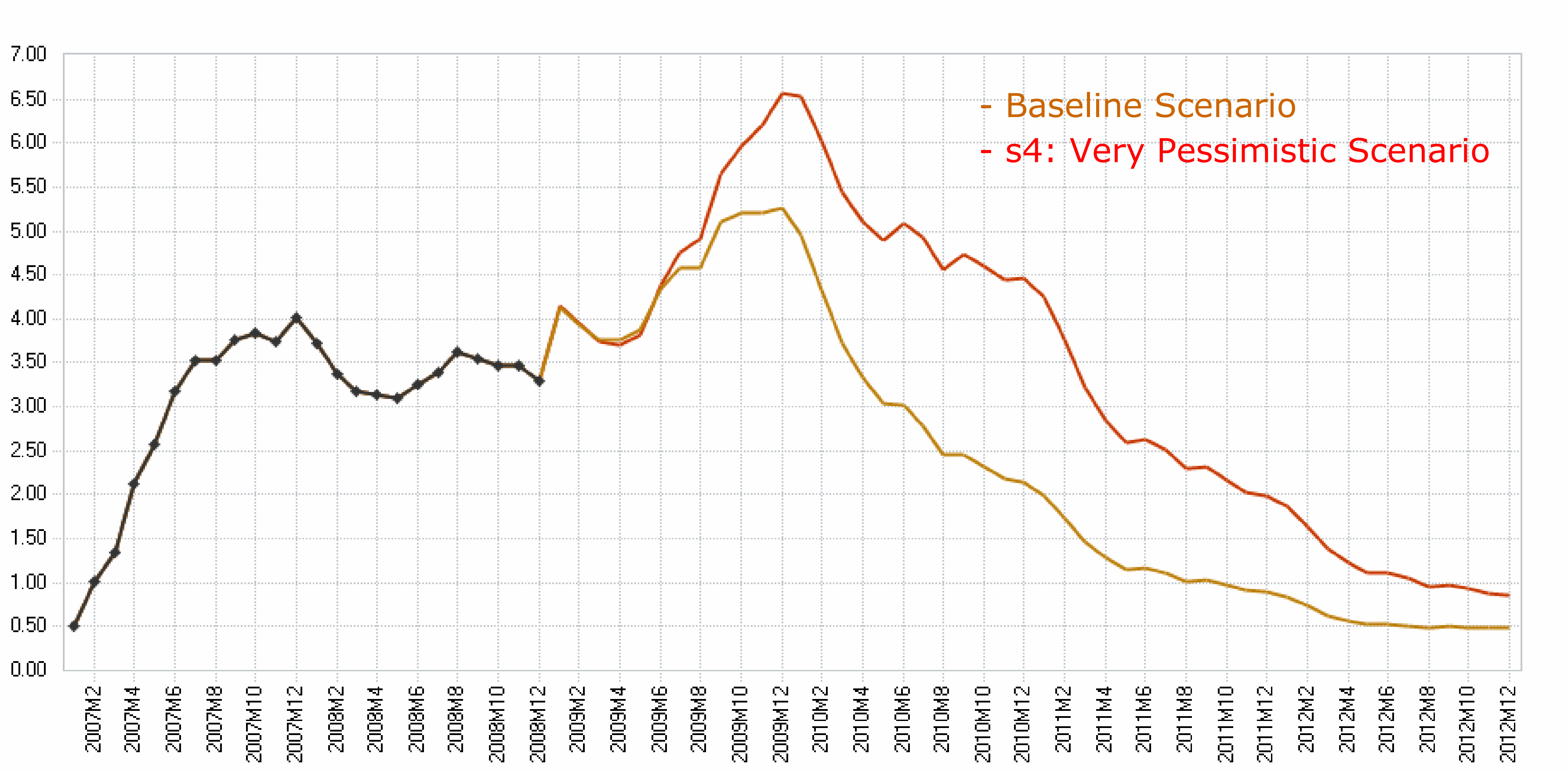


Consumer Credit Stress Testing

Modeling Approach

Exposure to the Business Cycle

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

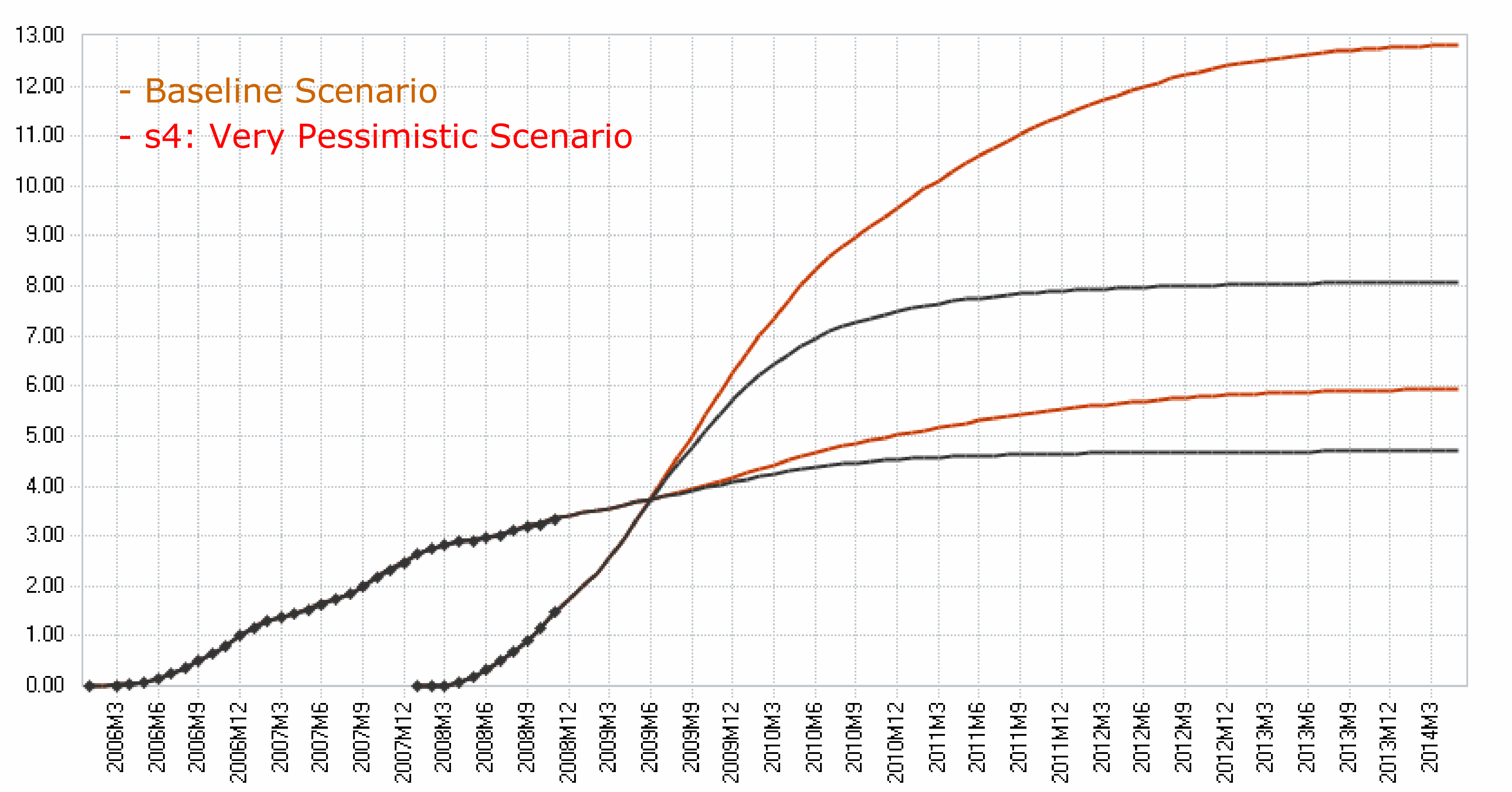


Consumer Credit Stress Testing

Modeling Approach

Exposure to the Business Cycle

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



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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

CALIBRATION AND CONSISTENCY

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.