



4.90

4.50

Big Data in Retail Lending



- With every great new technology, the biggest challenge is translating to practical value.
- Google is an artificial intelligence company
 - processing huge volumes of data
 - to make best-guesses on customer needs
 - where no "right answer" is known
 - with minimal regulation
 - This is an ideal use for the unstructured analysis of big data, but it is not the retail lending problem.

Data Analysis in Retail Lending



- The input data is highly regulated, with the same inputs available to all lenders.
- Insufficient history for unstructured macroeconomic analysis.
- The dominant structures in retail lending models are known. Unstructured analysis would be a disaster.
- Any AI-based result would never pass validation or examiner review.
- Any model output eventually rolls up to a finance report, involving even more layers of regulation and review.

The Opportunity of Big Data



- Using algorithms that allow for the incorporation of business expertise.
- Analyzing large data sets using model structures optimized for retail lending.
- Taking predictive analytics to the individual.

What are Predictive Analytics?



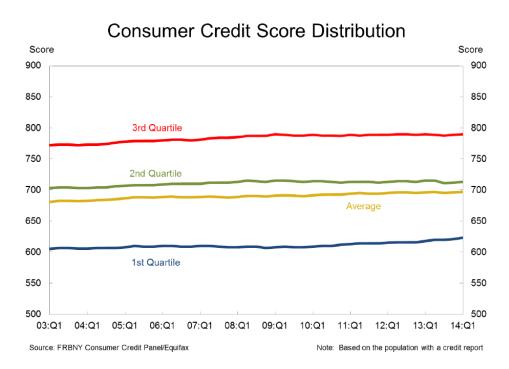
Seeing the future

Understanding the past

Predictive vs. Prescriptive

DFA DeepFuture Analytics

- Scores rank-order.
- FICO / Bureau scores measure overall risk on existing loans, not the risk after you give them a new loan. They don't measure product-specific risk or forward-looking risk.



Follow the Money...



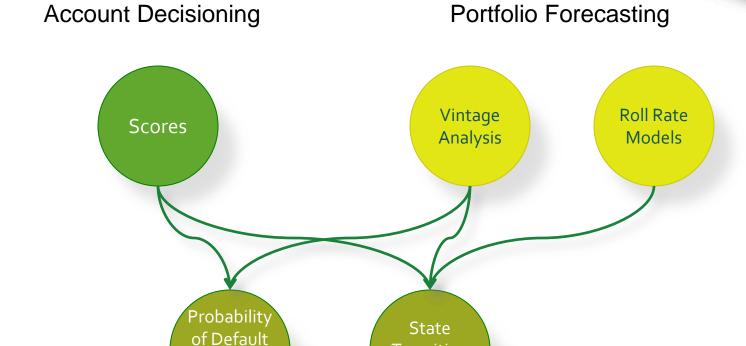
- The big analytics spends today are on regulatory compliance.
- The Fed, OCC, FDIC, and NCUA have all put forecasting and stress testing on center stage – predictive analytics.
- Examiner instructions to the biggest lenders: "You don't need loan-level models, but you need to build best-inclass models... Loan-level models are best-in-class."

The Next Generation in Modeling

(PD)

Models

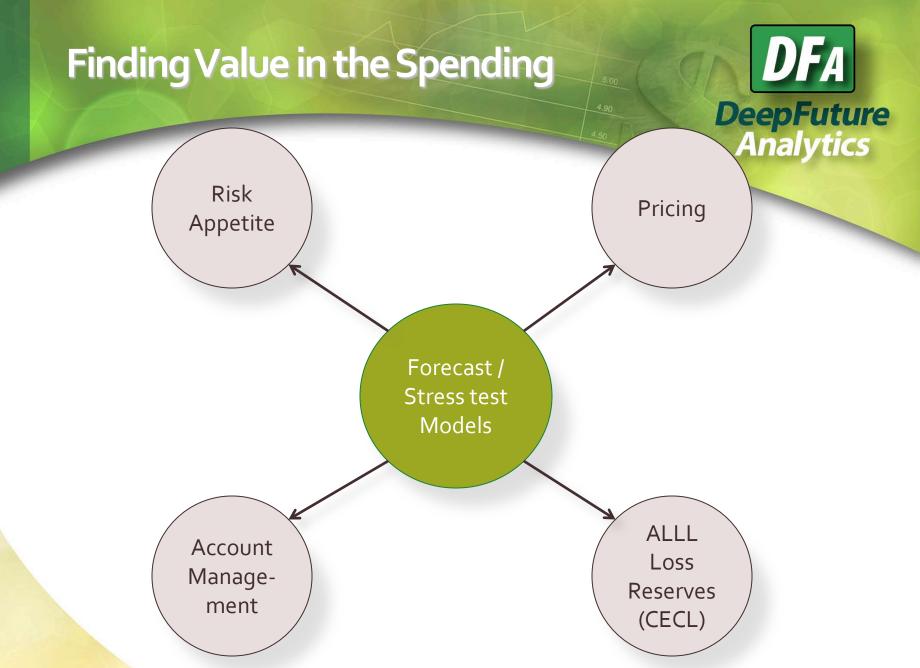




© 2014 Deep Future Analytics

Transition

Models



Pricing



- Pricing is often meet-the-market or moving average. In 2005, mortgage lenders were pricing based upon 2003 originations.
- Pricing often ignores loss timing. New loans are always low risk, but don't stay that way.
- Pricing models rarely consider the future environment or even the current or average environment.

Pricing Failures



- All banking crises are pricing failures first.
- The pricing model most likely to "break the bank" is "meet the market", but any approach can be done badly.
- In 2004 and 2005, mortgage lending executives were saying, "Grow the portfolio 40%, but don't drop the cut-off [FICO] score."
 - The result? Hard-working teams met their objectives earning big bonuses.
 - FICO tracking was constant.
 - Two to three years later, these portfolios collapsed from bad loans.
 - No one priced for the risk. They just priced for FICO.

Risk Appetite



How much of an economic downturn can I withstand before my new loans become unprofitable?

• All predictive models must consider future economic conditions. What conditions am I priced for?

Account Management



- Forward-looking probability models.
- Line assignment and next-sell based upon probabilities, not rankings

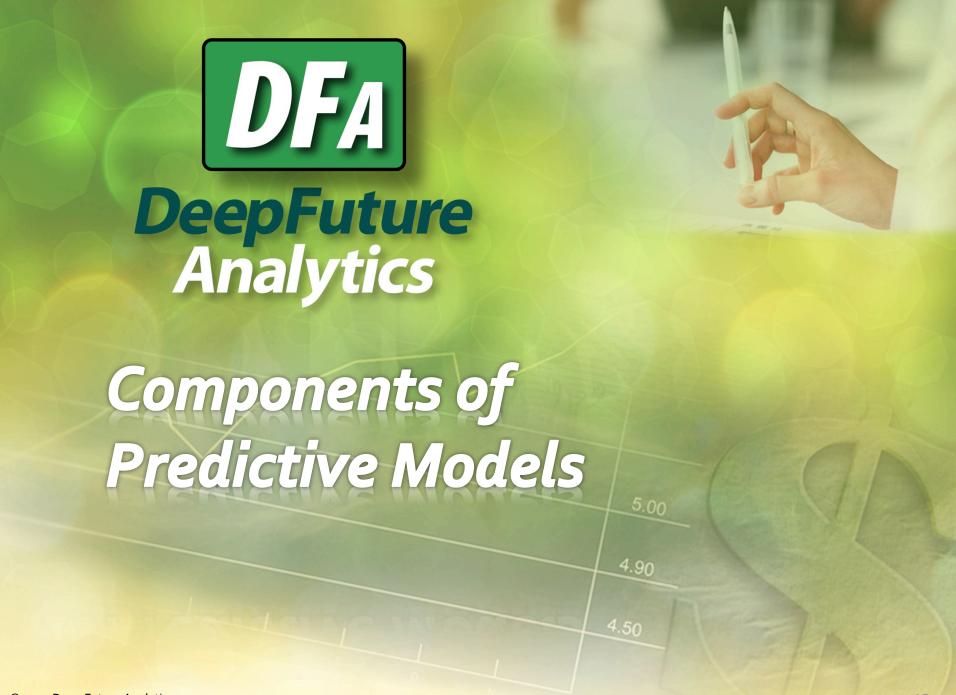
Competing risks: default versus prepayment

Loss Reserves



 ALLL models will finally become predictive models under CECL.

 Forecasting models, stress test models, and pricing models will all converge.



Moving to Quantitative Pricing

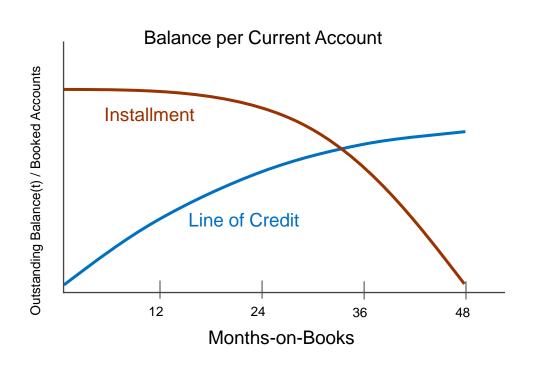


- Best practice is to estimate future margin quantitatively. Over the life of the loan.
- How will these evolve?
 - Balance growth / pay-down
 - Attrition / Prepayment risk
 - Loss timing
 - Credit risk
 - Future environment
 - Recoveries
 - Expenses

Balance Growth / Pay-down



- Balance dynamics are sensitive to the product, term, and segment.
- Balances are very dynamic through the life of the loan.



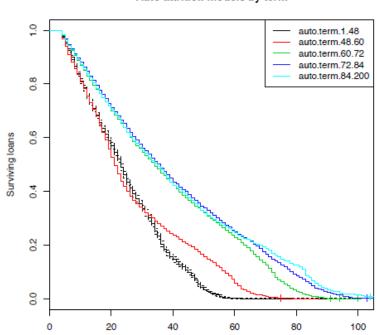
Prescient Modeling © 2013

Attrition / Pay-off



18

- How long will the loan be with us?
- Don't count the interest income in pricing if the loan pays off early.
- Different segments behave differently.



Prescient Modeling © 2013

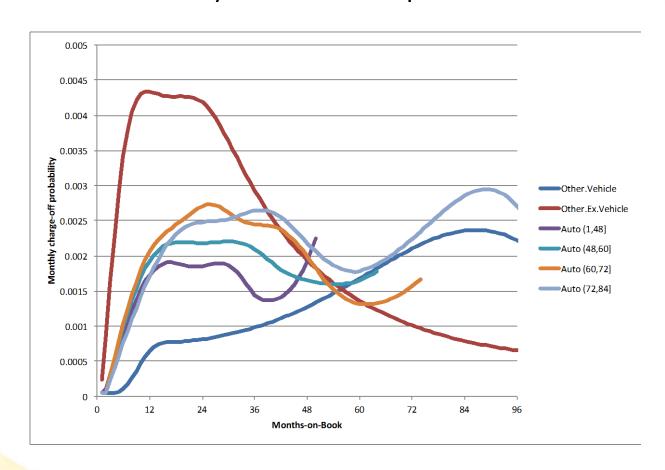
Age of the loan

Auto attrition models by term

Loss Timing



Do the losses come early or late in the product?



Deep Future Analytics © 2014

Credit Risk

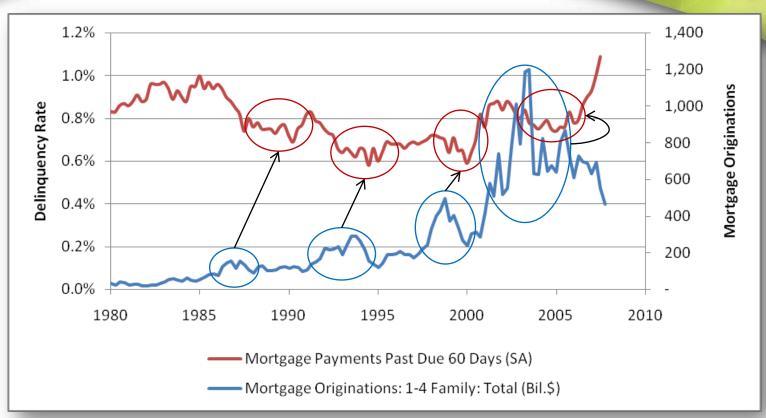


Credit risk is more than just FICO and LTV

- Product: Auto, Card, Mortgage
- Channel: Direct or Indirect
- Collateral: New, Used, None
- The CU relationship: Deposit Balance, Payroll
- Adverse selection

Modeling Through Cycles

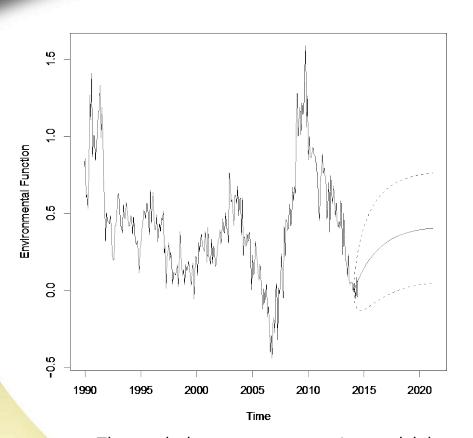




We can price loss trends, because even our own past booking volume patterns effect those trends.

The Future Environment





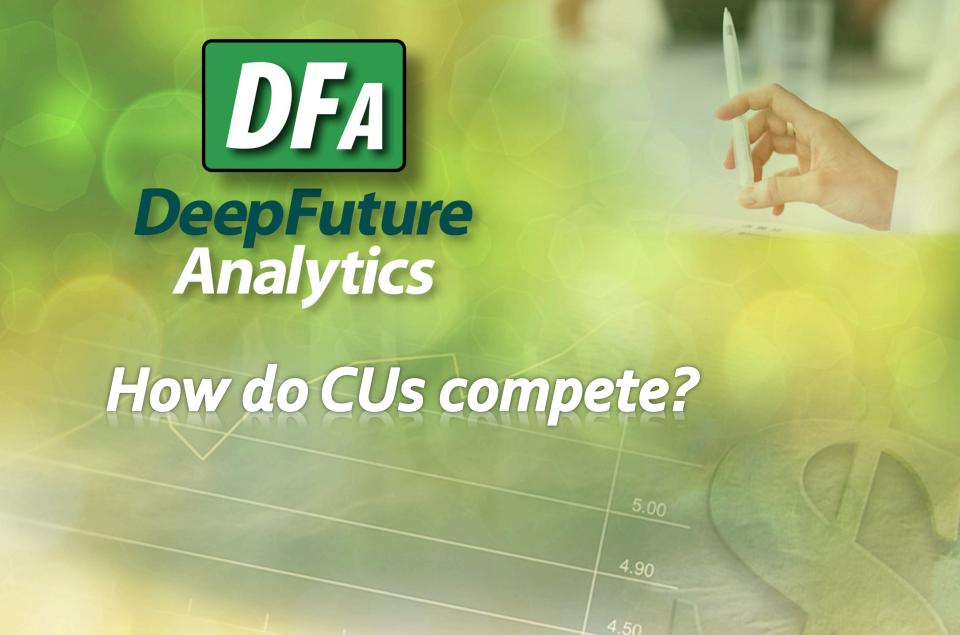
- Don't price for the past environment.
- Don't price for the current environment.
- Price for the near future and through the lifecycle

 consistent with CECL

 ALLL proposal.

The graph shows a mean-reverting model that relaxes the current economic environment onto the long-run average. This is input to a loss forecasting model for new originations.

Deep Future Analytics © 2014



Predictive Analytics for CUs



- As a regulatory requirement, 95% of the spend is on reporting and compliance.
- Build predictive models first for pricing at a fraction of the cost of regulatory compliance models.
- Pooled repositories across CUs can bridge the data gap.
- The first institution with a loan-level, forward-looking pricing model was a Credit Union.

Contact Us



- Deep Future Analytics provides margin forecasting as part of our analytics suite.
- Contact us at:

Dale Fosselman:

Email: dalef@denalifcu.com

Phone: 1-907-257-9494

Joe Breeden:

Email: <u>breeden@prescientmodels.com</u>

Phone: 1-505-670-7670