A Practical Approach to Building CCAR Loss Forecasting Models in SAS 9.3

Andre Toman

VP, Quantitative Risk Modeling Manager in Credit Risk

Advanced Modeling Team Lead

atoman@mtb.com

March 12th, 2014

Disclaimer

Any opinions, advice, statements, or other information or content expressed or made in the following presentation are those of the presenter.

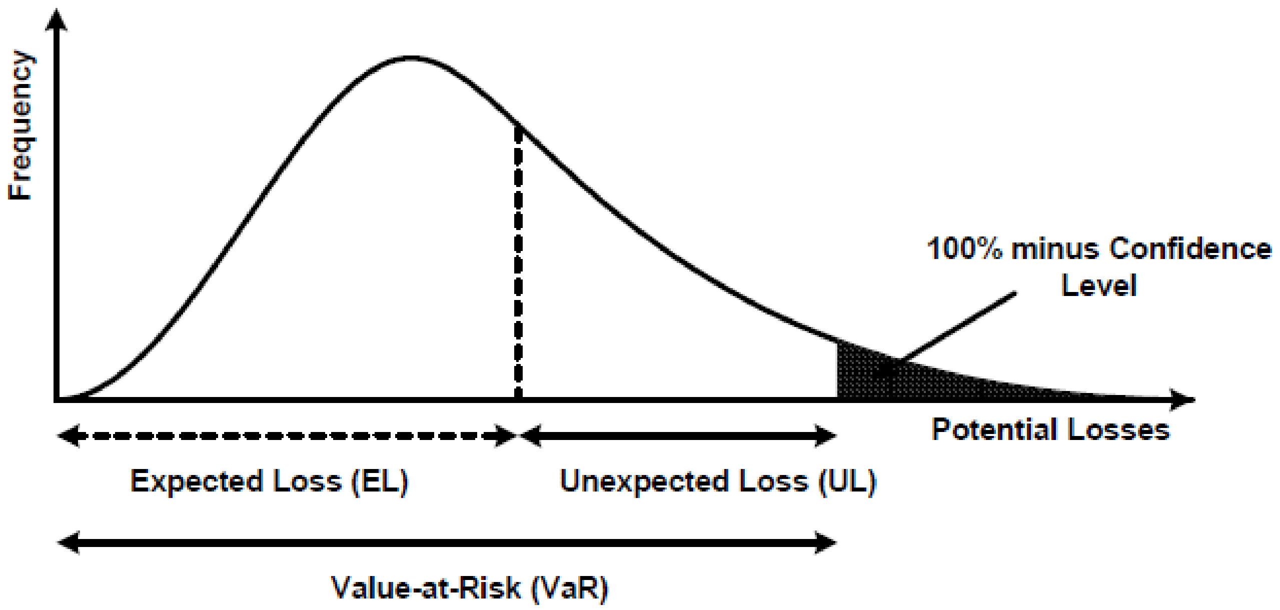
Overview

- Purpose of This Presentation
- Expected Loss Framework
- Model Fitting
- How the Model Works
- Backtesting Results
- CCAR 2015 Scenario Results
- Q&A

Purpose of This Presentation

- Decompose the stress testing modeling process for consumer portfolios into manageable components
- Provide examples that in whole, or in part, may be adapted to current modeling processes resulting in lift
- Provide a foundation of knowledge that can be useful to modeling shops that are beginning to build in-house stress testing solutions
- Motivate those interested in building in-house models, but who currently are beholden to expensive consultants or licensed black box software
- Pack what could have been 30 hours worth of material into 30 minutes the best I can
- Ultimately, give back to the SAS community from whom I was able to learn many skills and techniques that I've adopted for the purpose of building stress testing models

Expected Loss Framework



EL[1] = Probability of Default x Exposure at Default X Loss Given Default

Model each component separately

Balances, early payoff, prepayment, amortization, involuntary payoff, and the like are also important but not technically risk weight parameters. These will be needed for 9 quarter loss rate calculations.

1. "An Explanatory Note on the Basel II IRB Risk Weight Functions" http://www.bis.org/bcbs/irbriskweight.pdf

Model Fitting

Component†	Techniques to Consider	Available Model Fitting Procedures in SAS
PD	GEE, G-Side Random Effects, R-Side Random Effects, cubic splines	GENMOD, GLIMMIX, HPGENSLECT, HPLMIXED, REG, TRANSREG
EAD	Amortization schedules, cubic splines, credit conversion factors	Data step, REG, TRANSREG, SQL
LGD	Fractional Logit, Weighted Logistic Regression	GLIMMIX, LOGISTIC, NLMIXED, HPLMIXED, HPLOGISTIC
Payoff	Same as PD	Same as PD
Balances	Same as EAD	Same as EAD

†The Basel risk parameters will be the focus of this presentation, although many of the same techniques apply to payoff and balances

Model Fitting – Probability of Default

Step 1.

Business Knowledge (e.g., 350 <= FICO <= 850)
PROC FREQ for categorical variables
PROC UNIVARIATE for continuous variables
Identify key fields (balances, FICO, estimated loan-to-value, interest rates, line/loan terms, acquired vs. core, 141R/ SOP03-3, lien status, current delinquency state and next month's delinquency state, payoff date, chargeoff date, etc.)

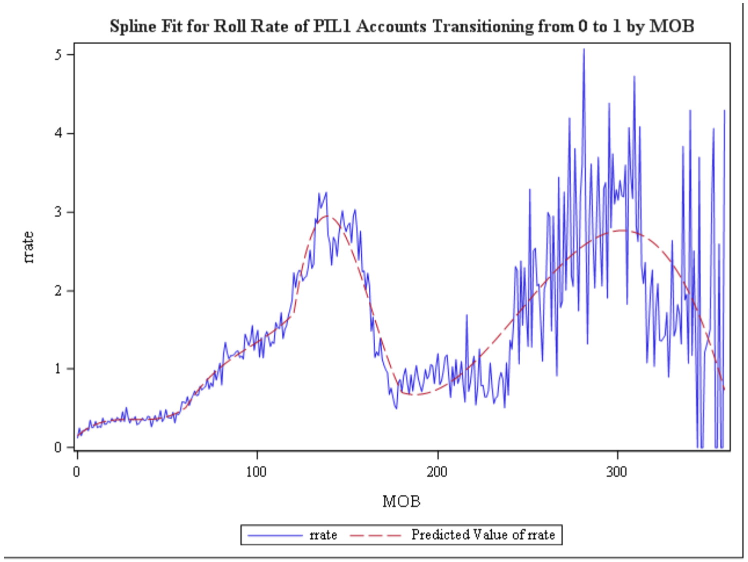
Step 2.

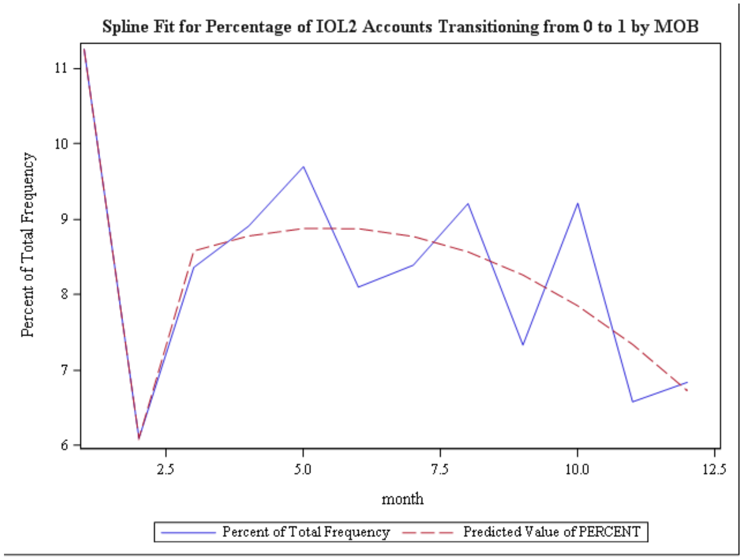
Examine the empirical migration matrix

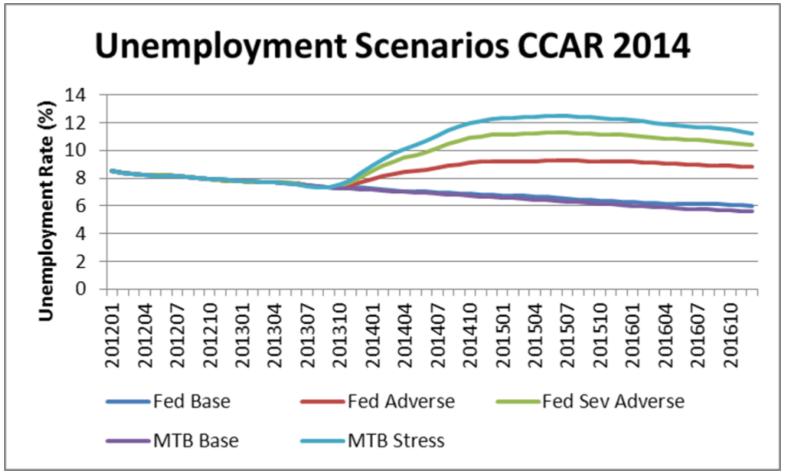
Table of Current Month's Status by Next Month's Status									
Current Delinquency Status (Payments Behind)	Next Month's Status (Payments Behind/Absorbing States)								
Row %	Current	1	2	3	4	5	Paid off	Charge off	Total
Current	97.67	1.68	0.00	0.00	0.00	0.00	0.64	0.01	
1	48.64	43.47	6.86	0.03	0.00	0.03	0.93	0.05	
2	17.77	25.30	24.40	31.02	0.00	0.00	1.51	0.00	
3	14.37	5.99	12.57	23.95	38.32	0.00	0.60	4.19	
4	3.23	1.08	2.15	8.60	10.75	44.09	0.00	30.11	
5	1.62	0.00	0.00	0.61	0.61	94.55	0.20	2.42	
Total	148212	4215	356	155	77	510	1001	58	154584

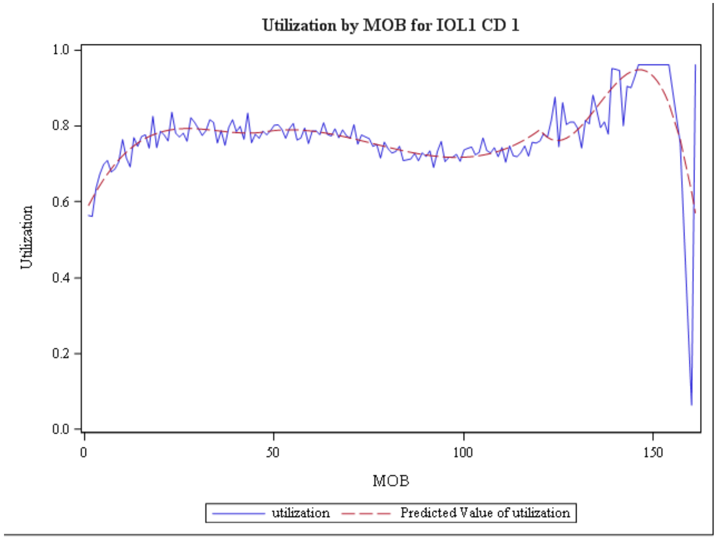
Model Fitting – Probability of Default

Step 3.
Independent Variables, create as necessary (lags, log ratios), use one continuous variable in place of class variables or many binary variables when possible.

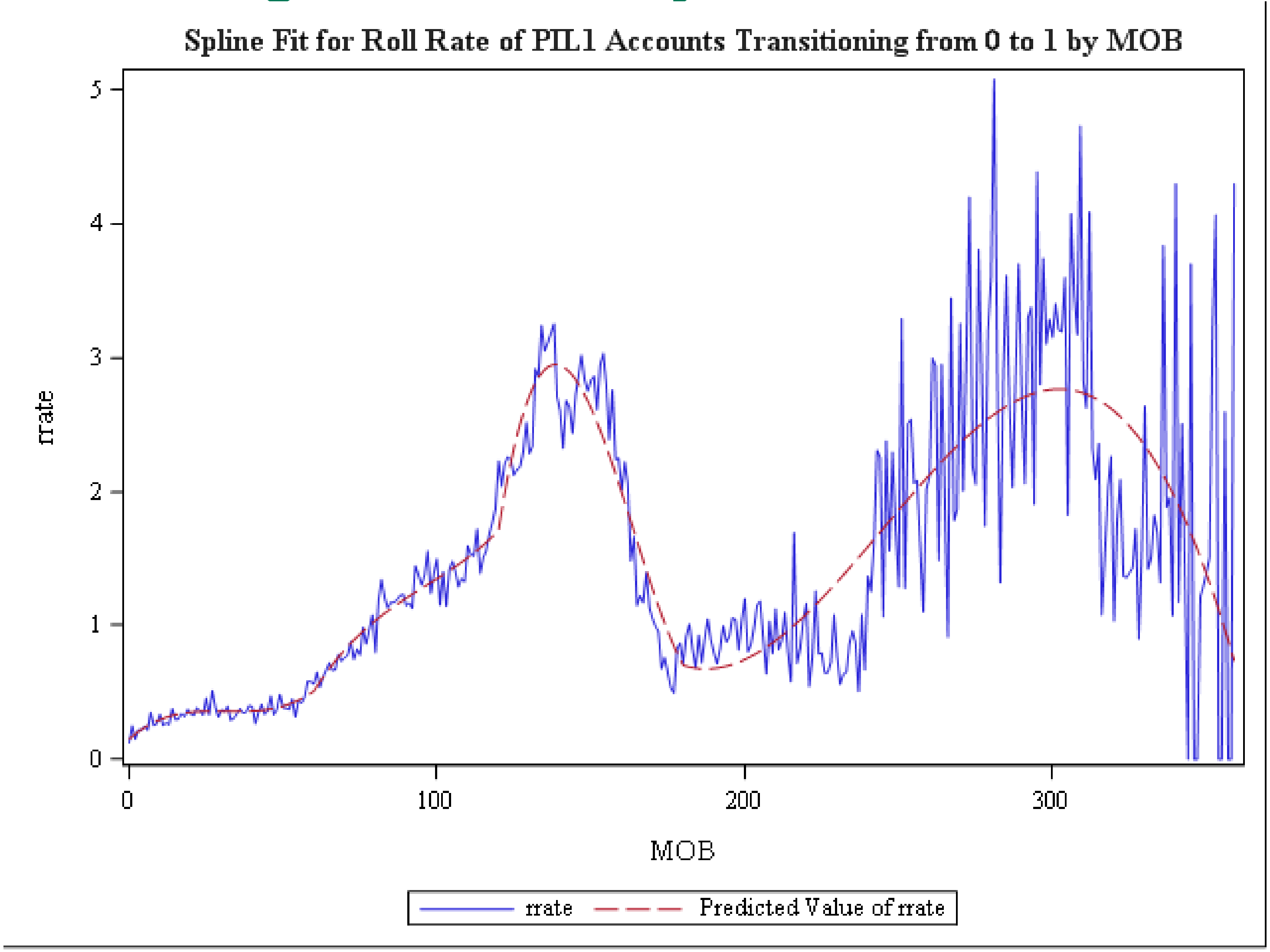








Model Fitting – Probability of Default



This is the “payment shock” phenomenon that the Fed is so concerned about!

Model Fitting – Probability of Default

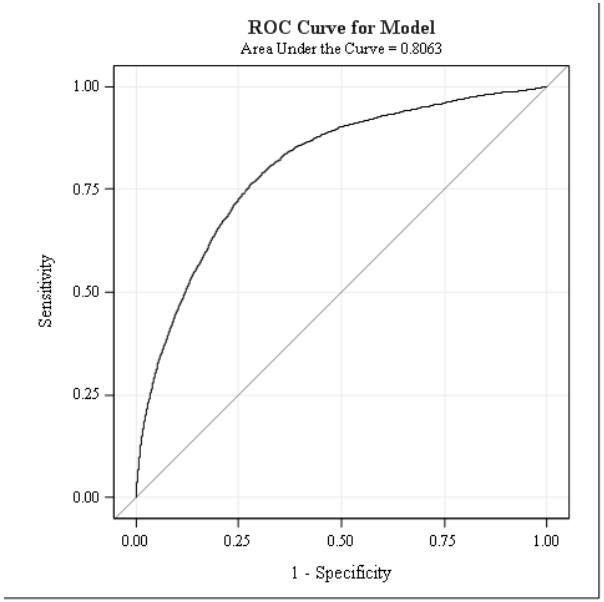
```
proc glimmix data=migration_&mig.;
        class FullAccountnumber Date;
        model transition_cd(ref="&c.")=
                Unemployment_rate
                HybridRescore
                Maturation
                Seasonal
        / dist=binary link=logit s;
        random _residual_ / subject=fullaccountnumber type=cs;
        store build.&lib._rside_&c._&m.;
run;
```

Step 4.

Fit and store the model for later use

(R-side random effects model shown)

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	-1.3155	0.1456	24259	-9.04	<.0001
Unemployment_rate	11.4376	0.5849	105E4	19.56	<.0001
HybridRescore	-0.00710	0.000181	105E4	-39.31	<.0001
Maturation	0.6141	0.01698	105E4	36.17	<.0001
Seasonal	0.1081	0.004626	105E4	23.37	<.0001

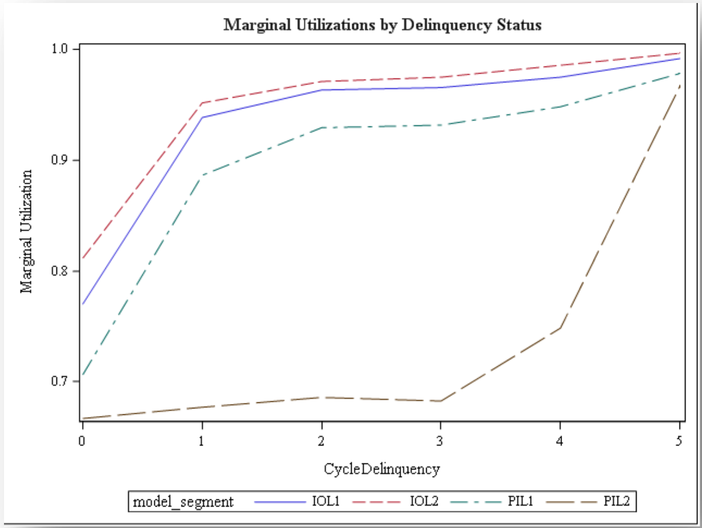


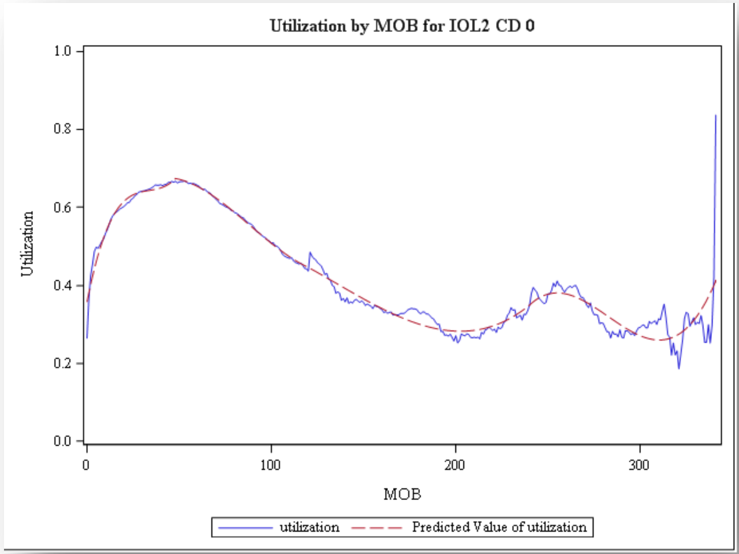
See the following SAS Press books for further information:
1. *Overdispersion Models in SAS* by Morel and Neerchal
2. *Logistic Regression Using:Theory and Application* SAS by Allison

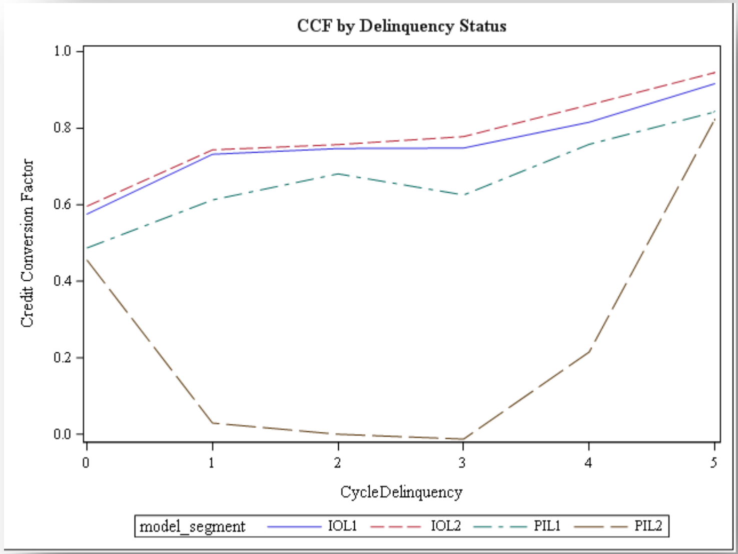
Model Fitting – Exposure at Default

Determine the appropriate methodology…

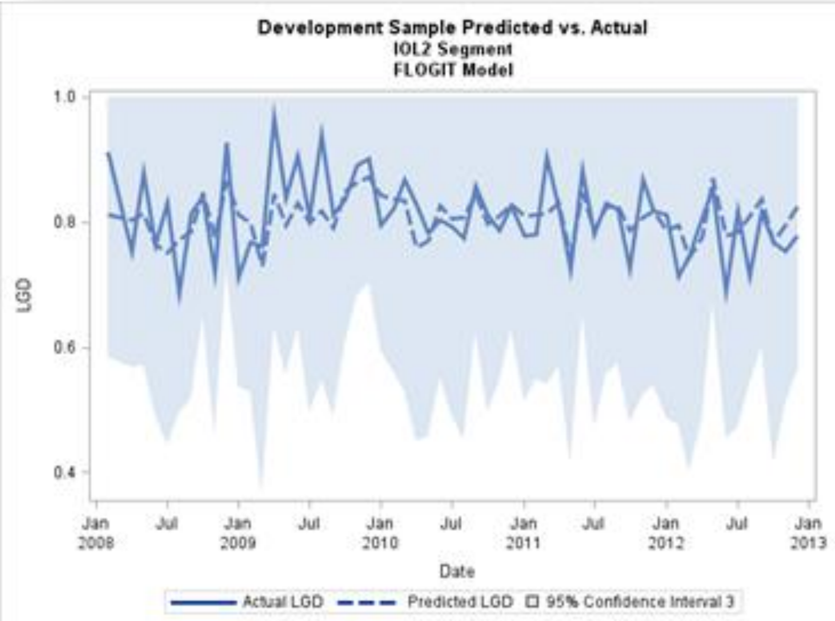
1. If it is installment, arithmetically calculate balance
2. If it is purely revolving, examine the marginal increase in utilization at each delinquency state, perhaps assume line is completely drawn at default, e.g., credit card
3. If it is a combination of both, e.g., home equity line of credit, take a hybrid approach
   a. Treat draw period as revolving as appropriate
   b. Treat repayment period as installment

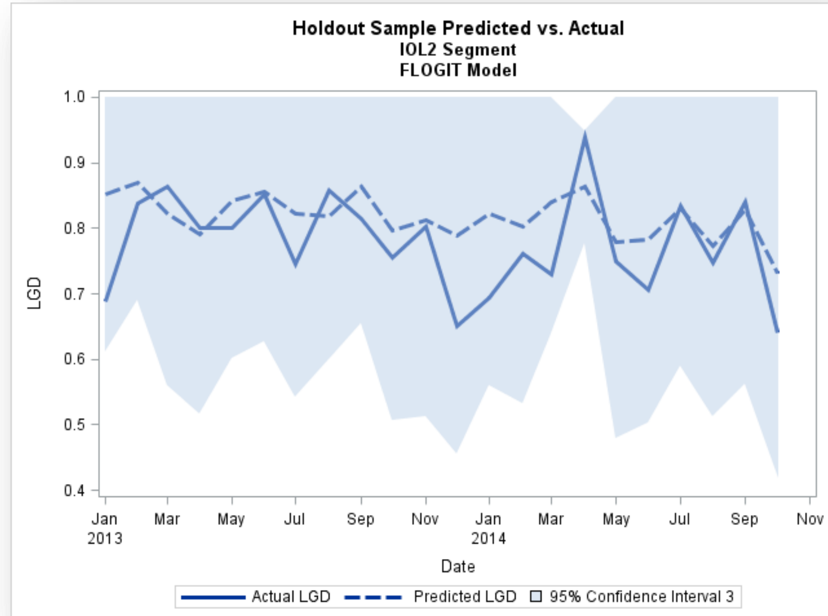






Model Fitting – Loss Given Default





Fractional Logit Model using the GLIMMIX Procedure					
Parameter Estimates					
Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	0.005231	0.2944	1556	0.02	0.9858
ECLTV	1.0732	0.2514	1556	4.27	<.0001
mtb_core	-0.7124	0.1994	1556	-3.57	0.0004
cd_03	1.4266	0.2565	1556	5.56	<.0001
cd_04	1.6525	0.1455	1556	11.36	<.0001

Weighted Logistic Model using the LOGISTIC Procedure					
Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	0.00523	0.2944	0.0003	0.9858
ECLTV	1	1.0732	0.2514	18.2277	<.0001
mtb_core	1	-0.7124	0.1994	12.7593	0.0004
cd_03	1	1.4266	0.2565	30.9323	<.0001
cd_04	1	1.6525	0.1455	128.9425	<.0001

Notice that the parameter estimates for the Fractional Logit and the Weighted Logistic Regression are the same. See SAS Paper 1304-2014 “Modeling Fractional Outcomes with SAS” by Liu and Xin for more information.

Modeler's Sidebar: Model Fitting Do's and Don't's

Andre's Model Fitting Tips	
Do…	Don't…
… write your own algorithms to test hundreds of thousands of models for model selection to ensure significance, proper sign, out-of-sample predictive power, and ultimately reduce model risk.	… use built-in automatic selection techniques† such as forward, backward, stepwise. I've seen too many times when the coefficients have the "wrong" sign, e.g., negative sign on unemployment to predict missing a payment.
… keep the transformations meaningful: log ratios of non-stationary variables, lags and log ratios of stationary variables. De-trend with log ratios where appropriate, e.g., use log(HPI/lag#(HPI)) vs. raw HPI or lags of HPI	… use lags much further back than 3, maybe 6 months. If you use a 39 month lag, the effect will never show up in the stress test!
… pre-screen macroeconomic variable combinations that exhibit a high degree of collinearity. Changes in HPI, unemployment rate, and 30 year mortgage rate, are highly collinear, not to mention other Fed variables.	… use LOGISITC for correlated data. You would be breaking all sorts of assumptions, and the models don't perform as well as models fit with GEE in GENMOD or R-side random effects models in GLIMMIX.

† See the following link for a balanced treatment of the benefits and drawbacks of using built in automatic selection techniques: http://support.sas.com/documentation/cdl/en/statug/63347/HTML/default/viewer.htm#statug_glmselect_sect019.htm

How the Model Works

Hypothetical Transition History for Account X

	Behavior For Account X	Jan-14	Feb-14	Mar-14	Apr-14	May-14	Jun-14	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14
		Month of Forecasting Period											
Delinquency State	State 0	X			X	X	X						
	State 1		X	X				X	X				
	State 2									X			
	State 3										X		
	State 4											X	
	State 5												
	State 6												
	State 7												X

Hypothetical Transition History for Account Y

	Behavior For Account Y	Jan-14	Feb-14	Mar-14	Apr-14	May-14	Jun-14	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14
		Month of Forecasting Period											
Delinquency State	State 0	Y	Y	Y									
	State 1												
	State 2												
	State 3												
	Staet 4												
	State 5												
	State 6				Y								
	State 7												

Hypothetical Transition History for Account Z

	Behavior For Account Z	Jan-14	Feb-14	Mar-14	Apr-14	May-14	Jun-14	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14
		Month of Forecasting Period											
Delinquency State	State 0	Z	Z	Z	Z	Z	Z	Z		Z	Z	Z	Z
	State 1								Z				
	State 2												
	State 3												
	Staet 4												
	State 5												
	State 6												
	State 7												

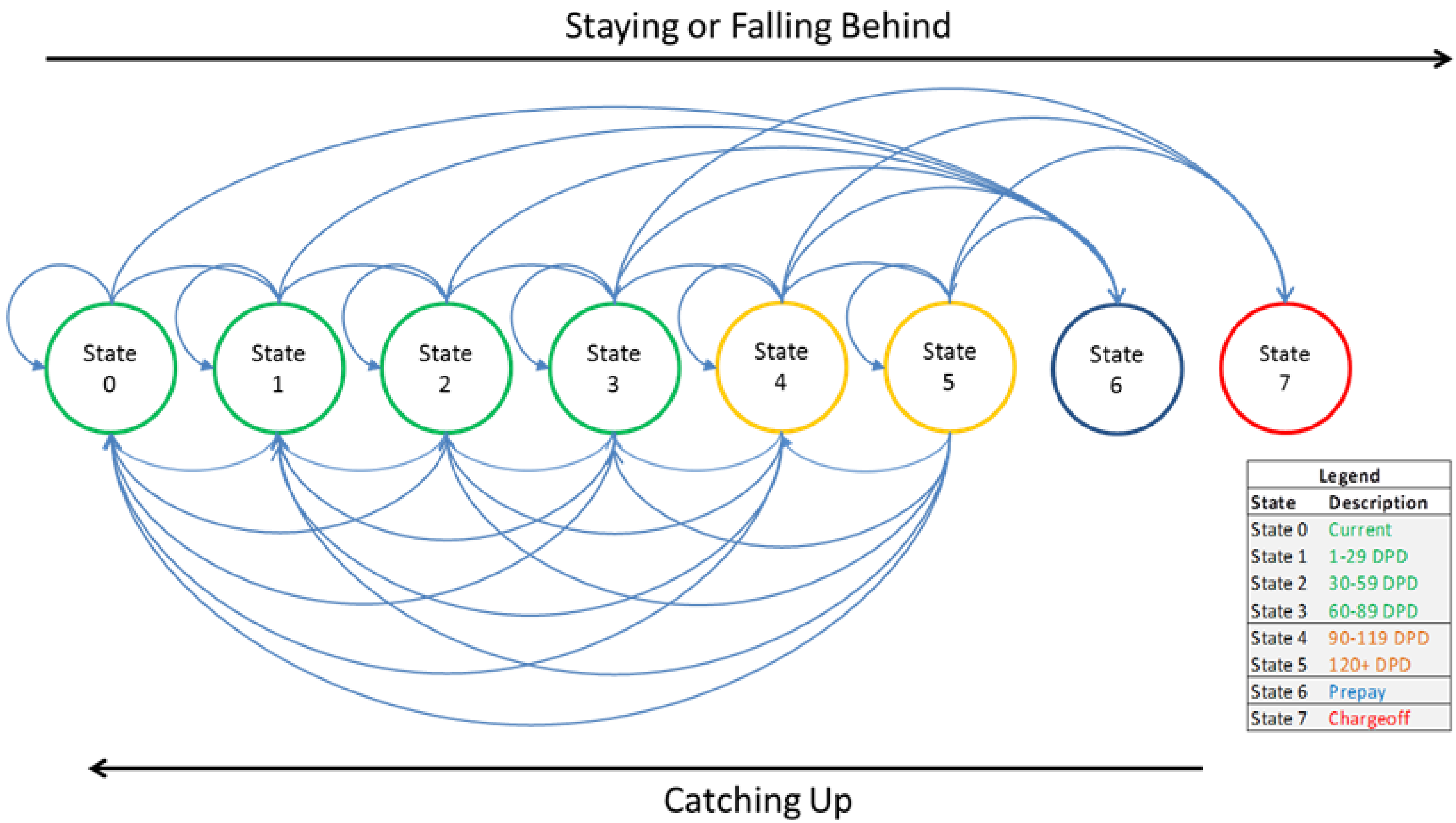
Legend

State	Description
State 0	Current
State 1	1 to 29 DPD
State 2	30 to 59 DPD
State 3	60 to 89 DPD
State 4	90 to 119 DPD
State 5	120+ DPD
State 6	Closed
State 7	Chargeoff
	Accrual
	Non-Accrual
	Absorbing State

Notes:
Account X Charges off
Account Y Closes
Account Z Performs

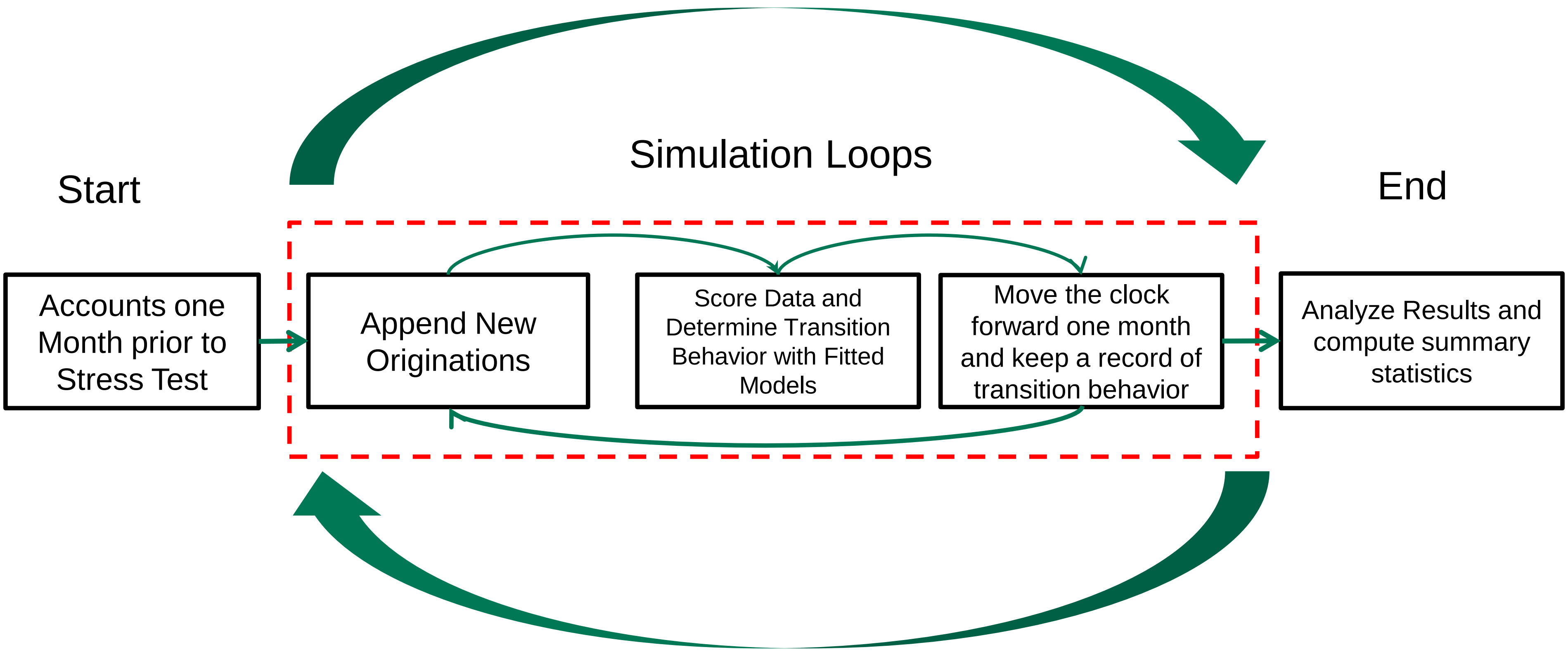
Accounts transition to various states from month to month

How the Model Works



We're not just looking at Account X, Y, or Z…We are looking at all accounts on the books and simultaneously forecast their transition behavior month to month based on loan-level and macroeconomic factors. Transition probabilities are converted to transition states using MCS. The process is repeated many times.

How the Model Works



Backtesting Results

Out-of-Sample 24 Month Backtest

CCAR 2015 Scenario Results†

†The model shown was not built before CCAR 2015, but the results shown were generated using the model and the CCAR 2015 idiosyncratic scenarios for M&T Bank.

Review

- Purpose of This Presentation
- Expected Loss Framework
- Model Fitting
- How the Model Works
- Backtesting Results
- CCAR 2015 Scenario Results
- Q&A

Special Thanks

- My beautiful wife and daughter for their support
- PhilaSUG for hosting this event and allowing me to present
- SAS for making the tools possible for my modeling projects

Questions and Answers