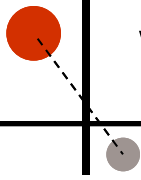


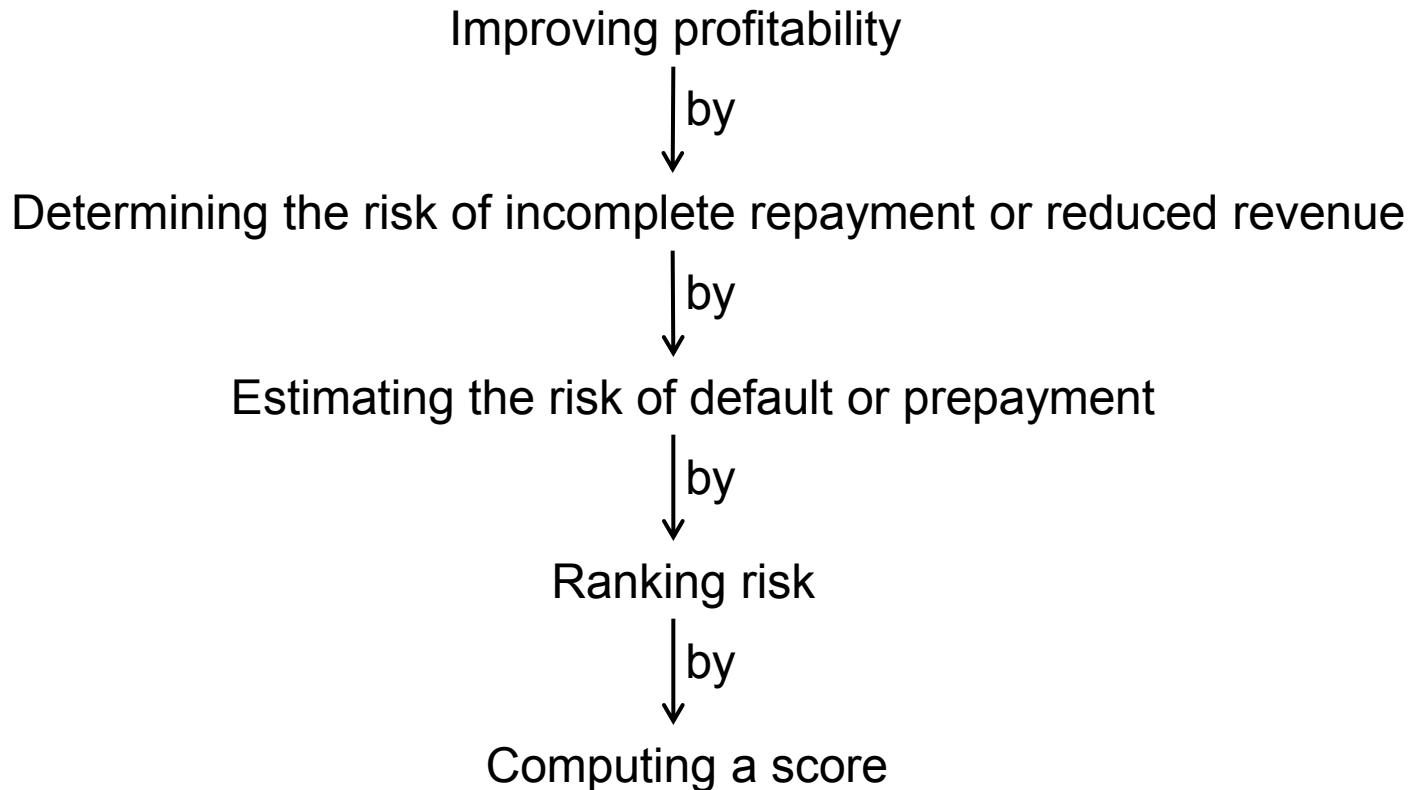
INCORPORATING LIFECYCLE AND ENVIRONMENT IN LOAN-LEVEL FORECASTS AND STRESS TESTS

Joseph L Breeden, PhD

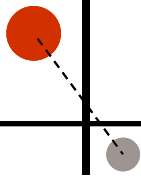




What are Scores for?



- This is the assumed hierarchy under which scores are created.



Profit Model

Cut-off Score 620

Max Loss _____

Max PD %

Exp. Revenue _____

Loan Amt _____

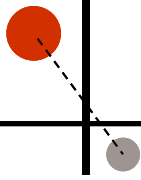
Expenses _____

EAD _____

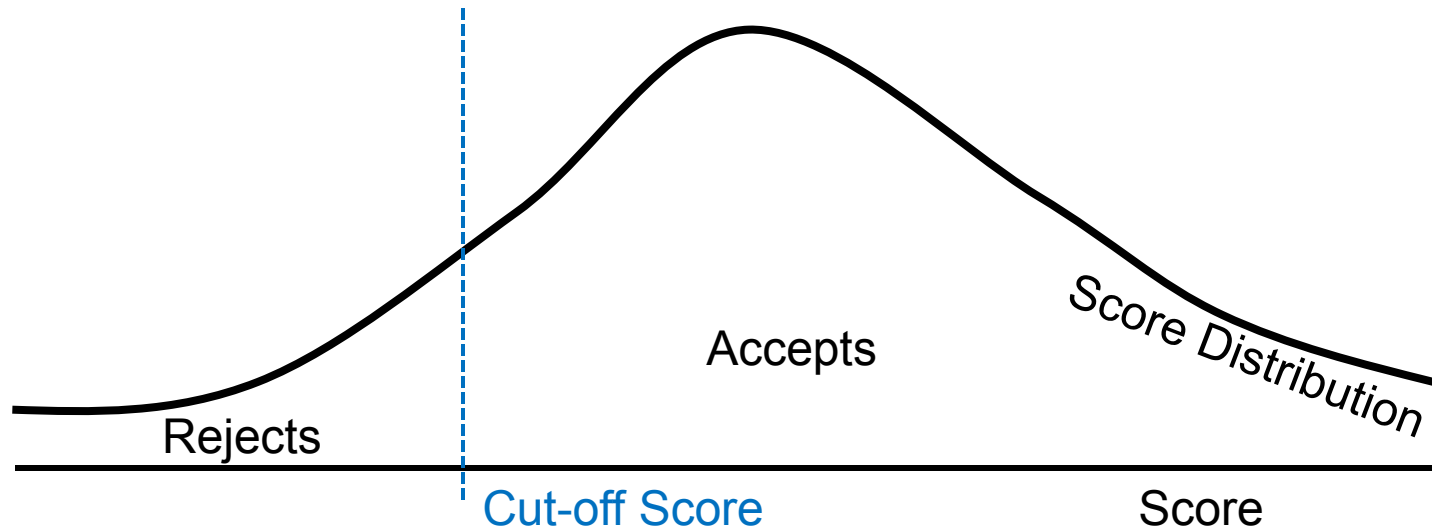
Min Margin _____

LGD _____

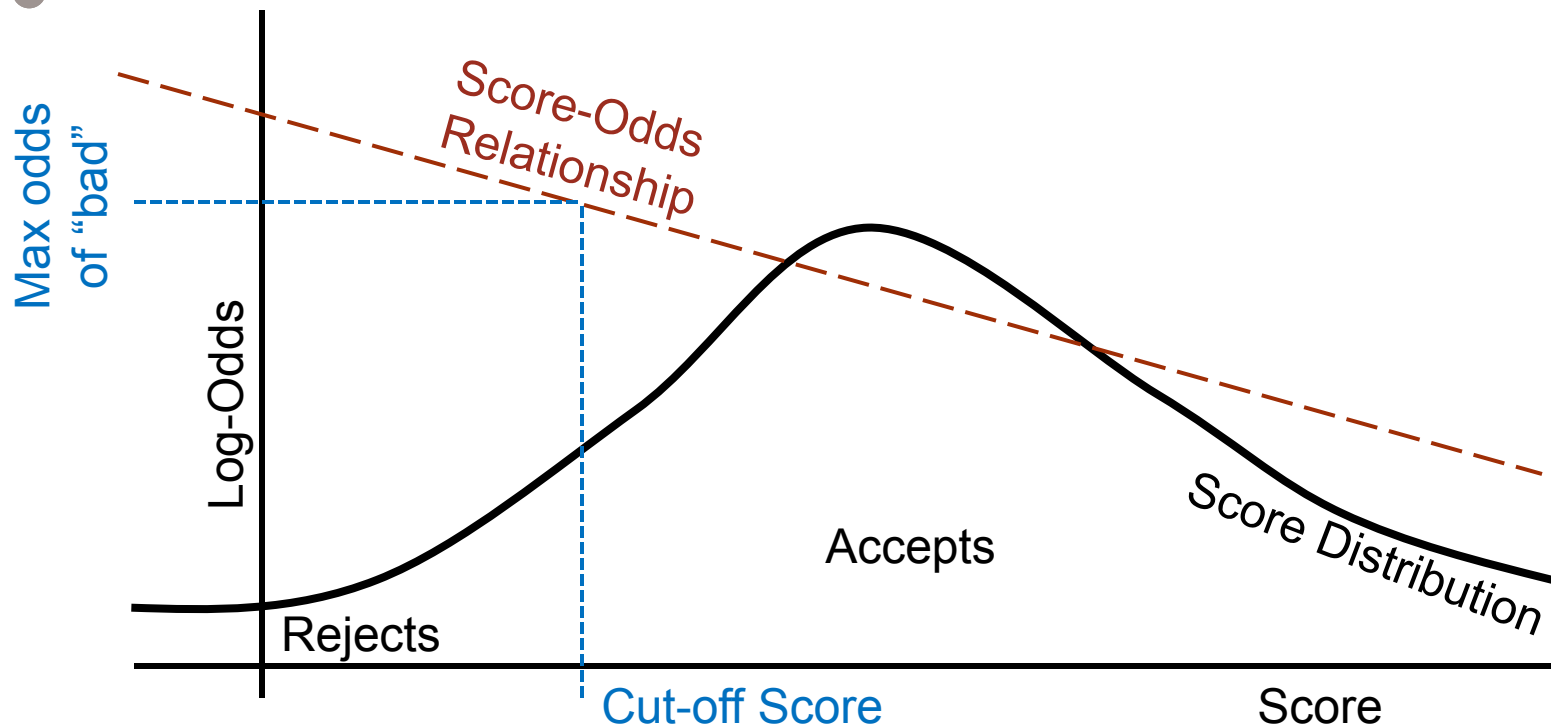
- The connection between cut-off score and PD is tenuous.
- We can be much more accurate in pricing if we start with a real PD forecast.



Using Scores: Setting Pricing



Using Scores: Setting Pricing



- The score distribution shifts with the economy.
- The score-odds relationship shifts with the economic cycle and credit cycle.
- Cut-off score is usually adjusted intuitively.



Standard Bank Practice

- Credit Risk has a group that builds scores that rank-order.
- Model Audit validates the scores rank-ordering ability.
- Credit Policy sets the cut-off score to control risk (odds of default).
- Finance creates a profit model that assumes a certain odds of default.

This structure fails by design.

What we needed from the start was a probability model.

Any score provides that in-sample, but how do we produce it out of sample?



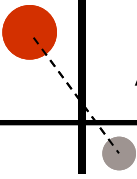
MODELING PROBABILITIES





Drivers of Performance

- *Origination*: Consumer & loan information.
- *Vintages*: Biases for specific cohorts.
- *Lifecycle*: Changes with age of the loan.
- *Behavior*: As the loan matures, observed loan performance can refine the predictions.
- *Account Management*: Changes made to individual loans.
- *Environment*: Changes in the economy or portfolio management.
- *Loan Idiosyncratic Effects*: Every loan is unique.



Age-Vintage-Time (A-V-T) Dependency

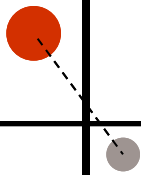
Information Type	...is a function of
Originations	Recent history or loan (i) up to origination date (v)
Vintage	Vintage origination date (v)
Lifecycle	Age of the loan (a)
Behavior	All time since origination (v, v+1, ... , t=v+a)
Account Management	Time since event (t_e)
Environment	Recent time (t-n, ... t-1, t)
Loan Idiosyncrities	Loan (i)

- Because $a = t - v$, measurements from one information source will be contaminated by other sources:
 - Behavior is dependent on Lifecycle and Environment.
 - The linear components of any vintage, age, or time dependencies cannot be uniquely measure.



Modeling Implications

- From the Age-Period-Cohort literature, we know that *linear* effects in age, vintage, and time cannot be uniquely determined regardless of the model used.
- For short data sets (such as a typical 2-year scoring dataset), the macroeconomic environment by time and credit risk by vintage are mostly linear trends.
- Coefficients estimated against the linear components of macroeconomic variables and scoring factors will be unstable, i.e. **adding macroeconomic factors to scoring models rarely works.**



GLM-AVT Model

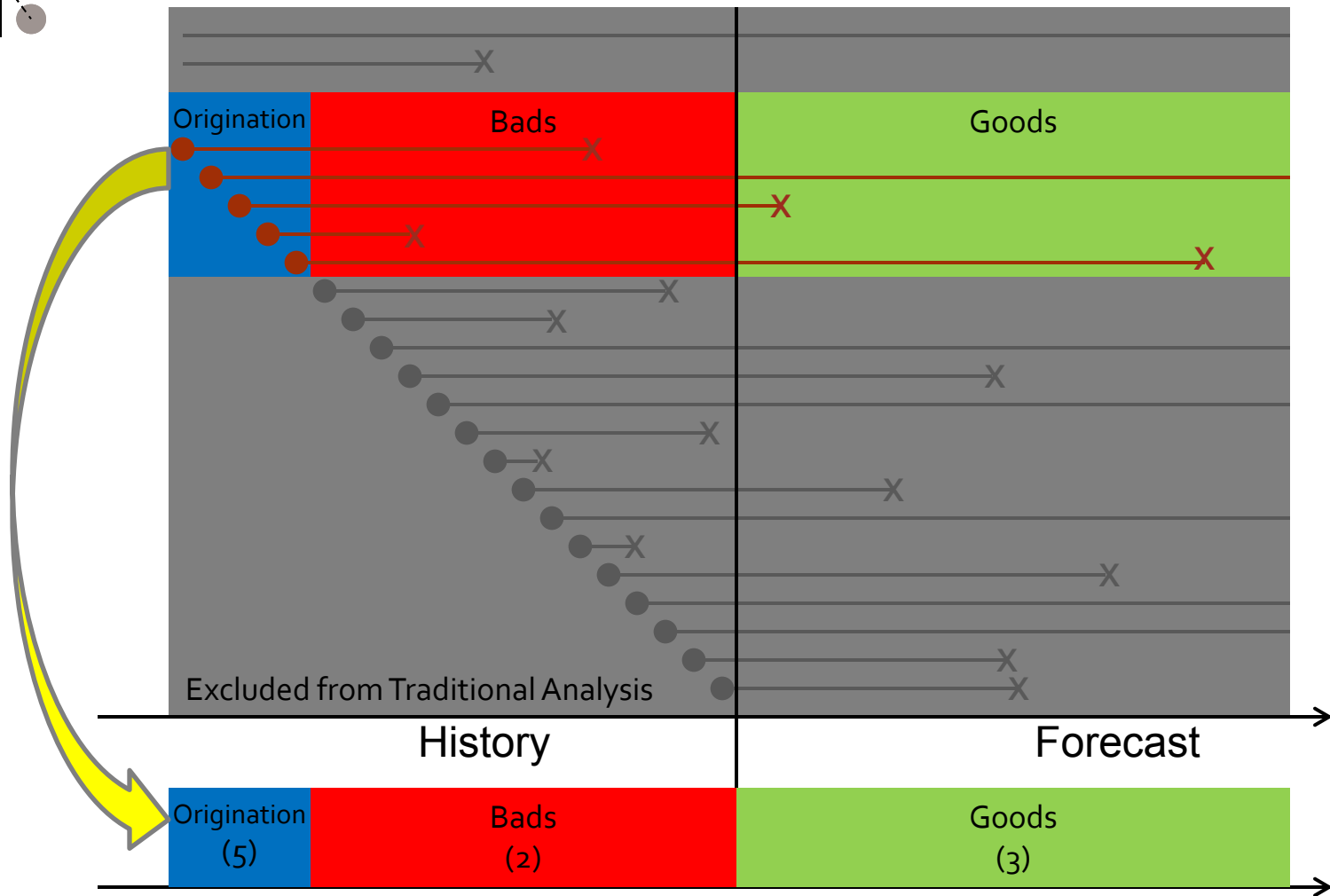
1. Use the Age-Vintage-Time structure found in APC, but in a loan-level model.

$$\log \frac{p_i(a, v, t)}{1 - p_i(a, v, t)} = f(a) + g(v) + h(t), \quad a = t - v$$

Make an explicit choice about trend allocation between $f(a)$, $g(v)$, and $h(t)$ to obtain a unique solution.

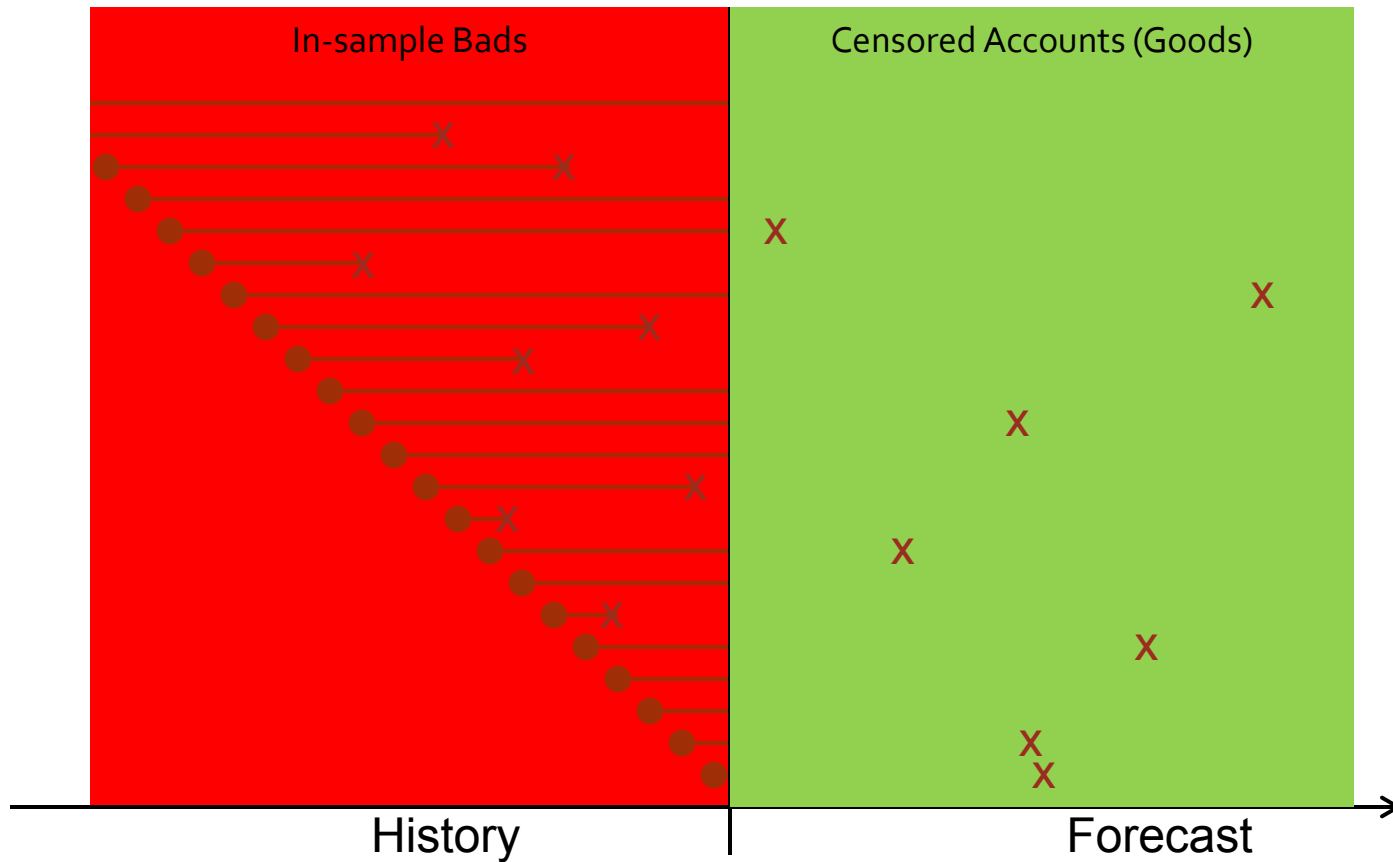
1. (Optional) Fit $h(t)$ to macroeconomic data. Retrend lifecycle and credit risk trends to compensate.
2. Introduce either origination or behavioral scoring factors to estimate score.

Data for Loan-level Modeling



- A standard approach to defining Good and Bad accounts for logistic-style regression without inclusion of temporal information.

Data for V-A-T Decomposition Methods



- All in-sample loans are included in analysis with emphasis on time of Event occurrence.
- Goods are simply accounts that were not observed to go bad. They are included as censored accounts in the estimation process.

1. Create Loan-level Age-Vintage-Time Model

Put an APC structure into a loan-level GLMM framework.

$$\log \frac{p_i(a, v, t)}{1 - p_i(a, v, t)} = \alpha_0 + \alpha_1 a + \sum_{j=2}^{N_a-1} \alpha_j O_j(a) + \beta_1 v + \sum_{j=2}^{N_v-1} \beta_j O_j(v) + \sum_{j=2}^{N_t-1} \gamma_j O_j(t)$$

- 1 constant term, 2 linear terms, and nonlinear terms in a , v , and t . No explicit cross-terms.
- O_i are orthogonal basis functions.
- N_a , N_v , and N_t are the number of observations in a , v , and t .
- Assumes environmental trend = 0.



Create Age-Vintage-Time Functions

Recast as functions $F(a), G(v), H(t)$ as

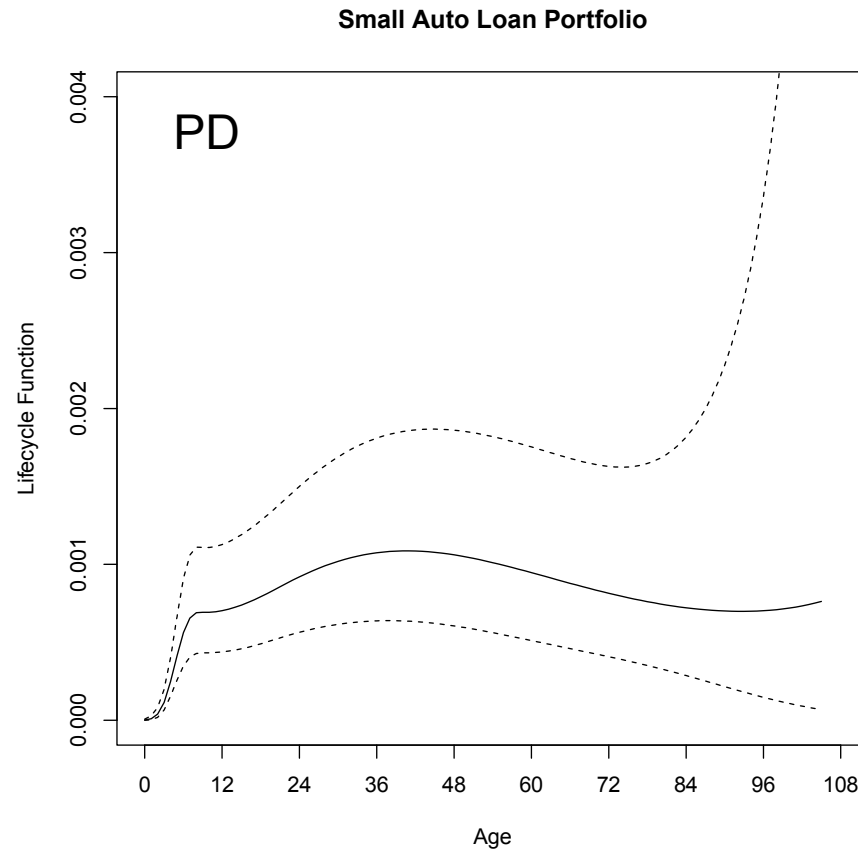
$$F(a) = \alpha_0 + \alpha_1 a + \sum_{j=2}^{N_a-1} \alpha_j O_j(a)$$

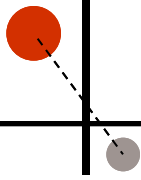
$$G(v) = \beta_1 v + \sum_{j=2}^{N_v-1} \beta_j O_j(v)$$

$$H(t) = \sum_{j=2}^{N_t-1} \gamma_j O_j(t)$$

Example

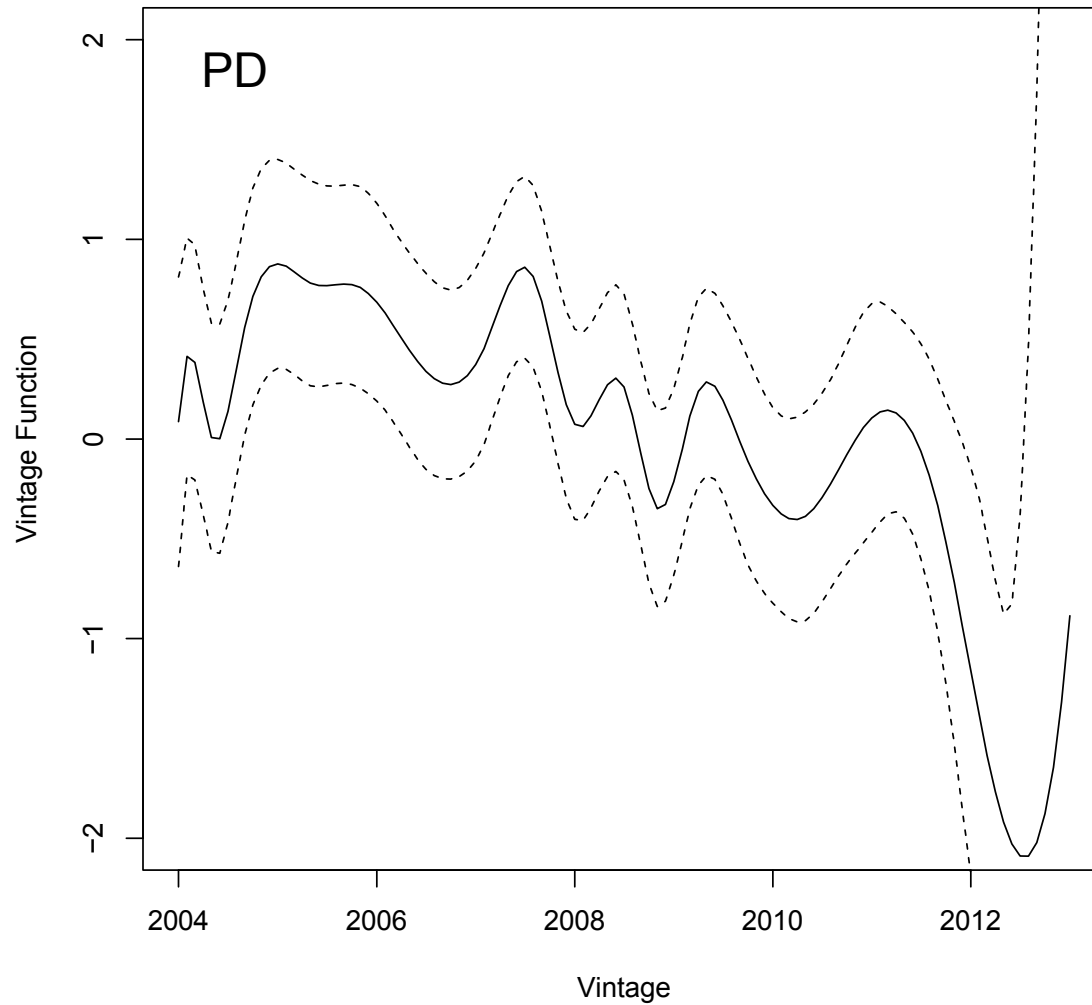
- Regional US auto loan portfolio, ~\$400 mln receivables.
- We modeled PD, EAD, LGD, and attrition to predict losses.

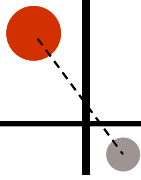




Credit Risk Function Example

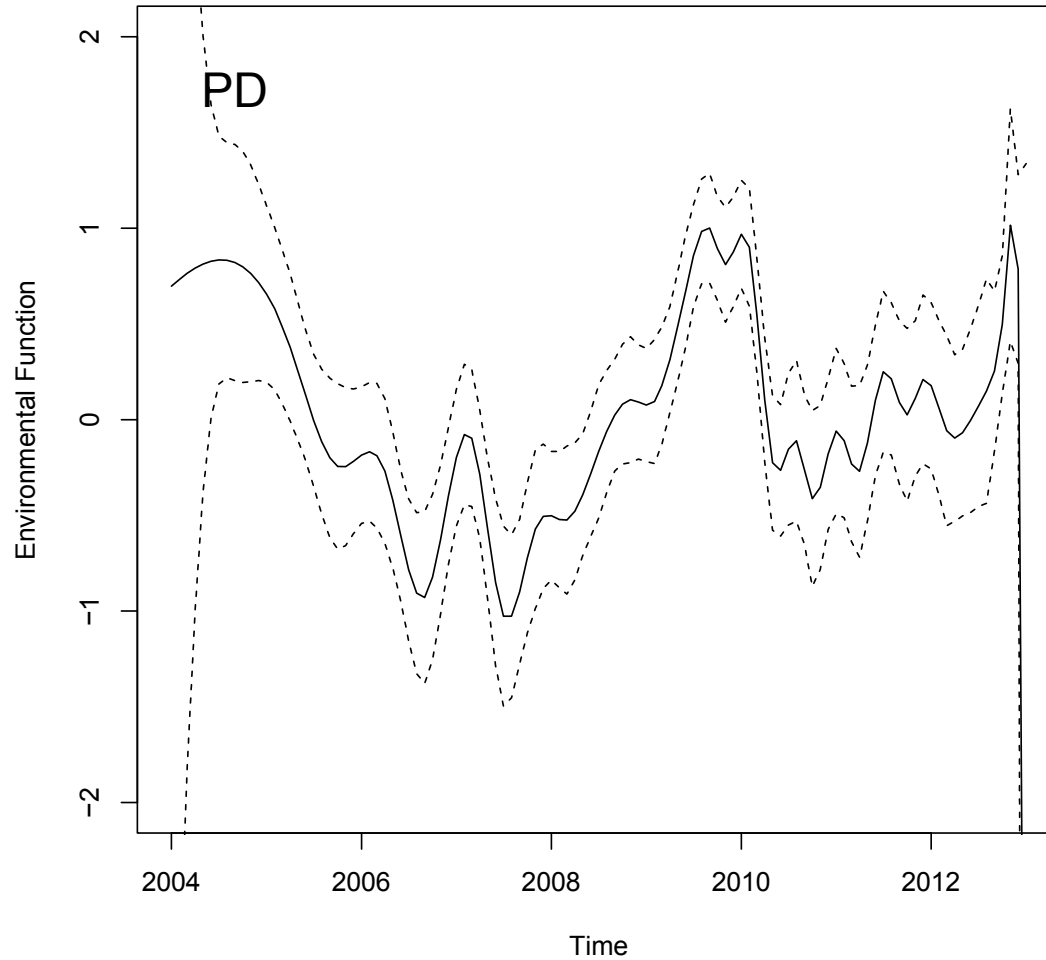
Small Auto Loan Portfolio





Environment Function Example

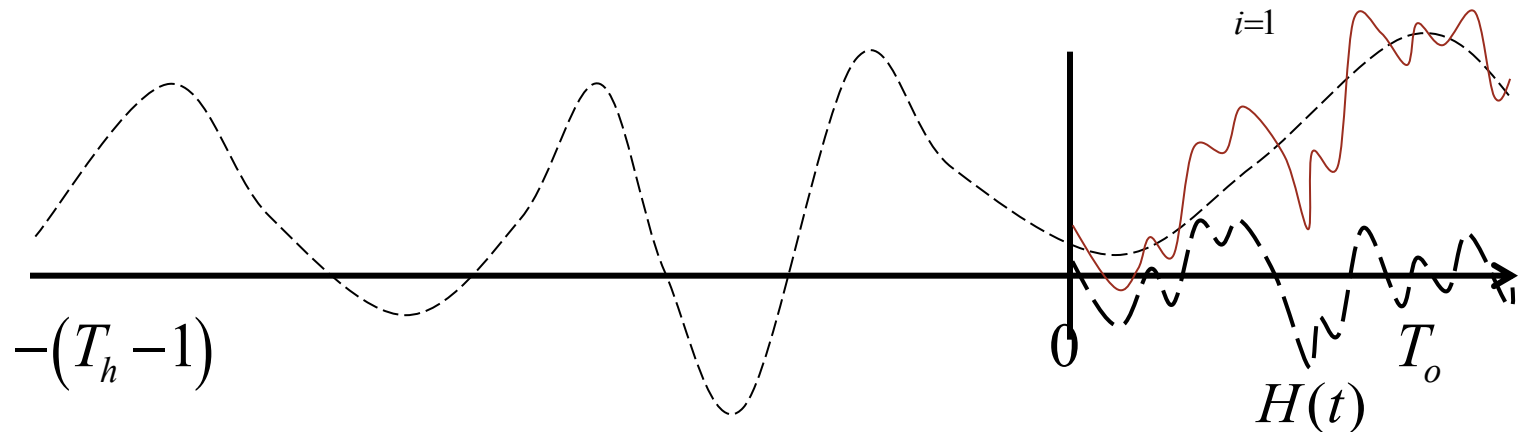
Small Auto Loan Portfolio



2. Fit to Macroeconomic Data

Create OLS fit of $H(t)$ to macroeconomic factors $E_i(t)$ with an explicit trend term. Possibly use a constrained fit so the long-run trend = 0.

$$H(t) = c_0 t + \sum_{i=1}^N c_i E_i(t) + \varepsilon$$



- We have T_0 observations of function $H(t)$.
- We have T_h measurements of n economic factors $E_i(t)$ prior to the start of the performance data.
- Total length of economic data is $T = T_0 + T_h$.



Create a macroeconomic model

- Model just the environmental function with macroeconomic factors. (Macroeconomic adverse selection impacts on vintage quality is a separate effect.)
- Use the correct transformations: log-ratio, not % change; log interest rates; etc.
- Allow for a linear component.

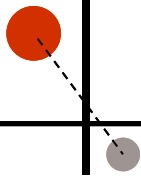
	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	5.908513	1.250051	4.727	3.31E-06
t	-0.009547	0.002535	-3.765	0.000195
Unemp.lwMovingAvg.Lm6.W3	2.050558	0.535645	3.828	0.000153
HPI.lwLogRatio.L5.W24	-2.262367	1.039257	-2.177	0.030153
Housing.Starts.lwLogRatio.L8.W15	-0.306789	0.047639	-6.44	3.94E-10

Residual standard error: 0.434 on 351 degrees of freedom

(12 observations deleted due to missingness)

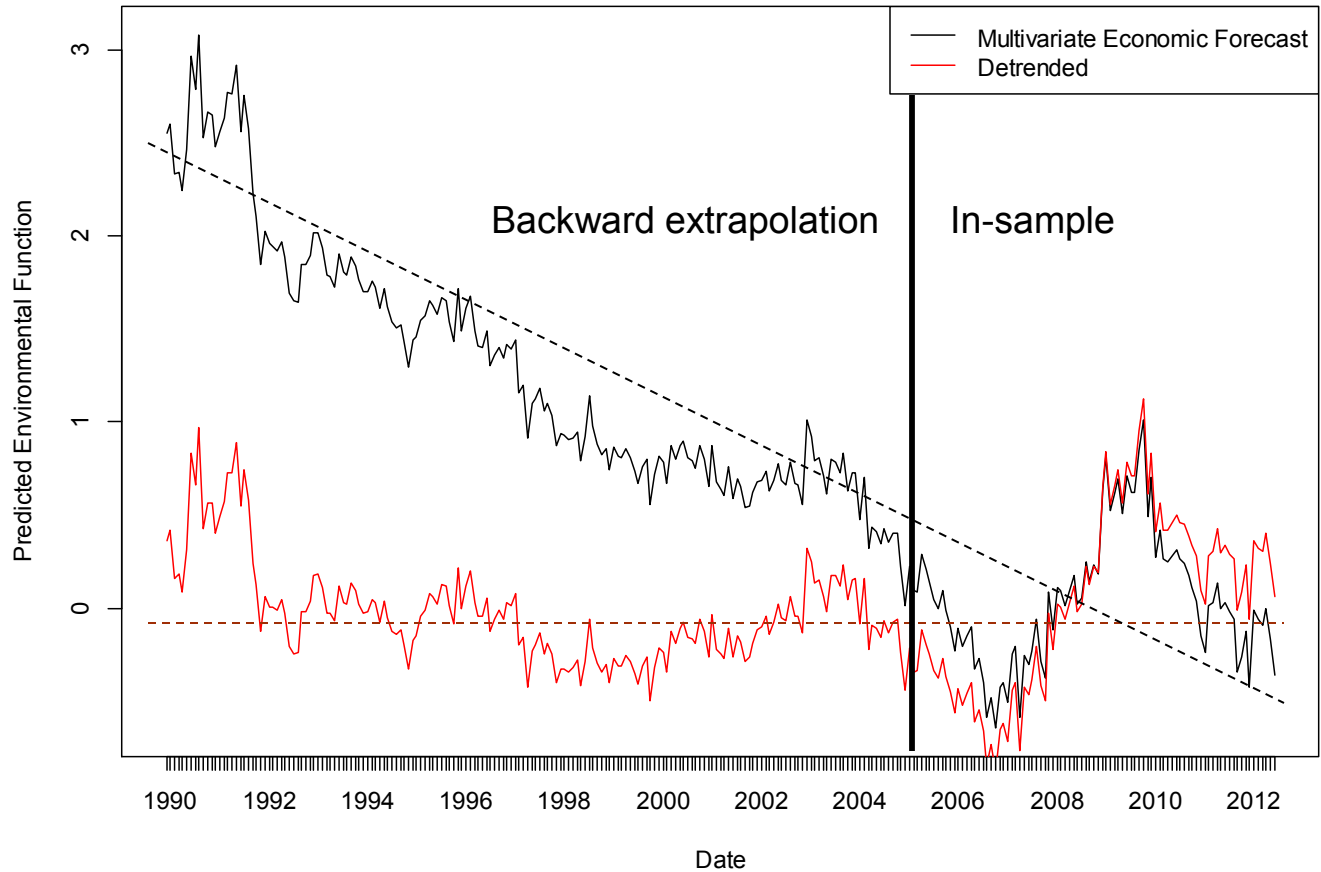
Multiple R-squared: 0.3918, Adjusted R-squared: 0.3848

F-statistic: 56.52 on 4 and 351 DF, p-value: < 2.2e-16



Retrend the environmental function

Multivariate Forecast of Environmental Function for All Products





Readjust Age-Vintage-Time Functions

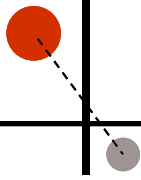
Compensate for the trend in $H(t)$.

$$F'(a) = F(a) + c_0 t$$

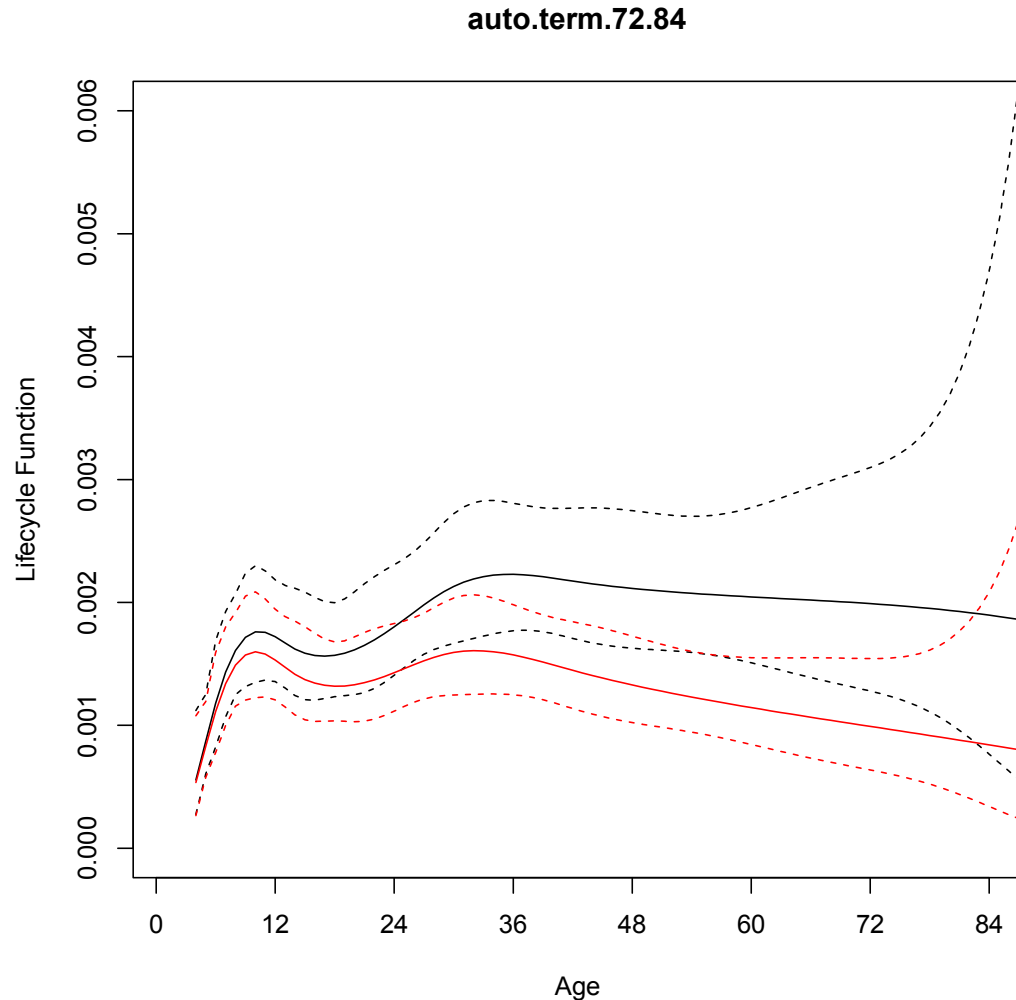
$$G'(v) = G(v) + c_0 t$$

$$H'(t) = H(t) - c_0 t = \sum_{i=1}^N c_i E_i(t) + \varepsilon$$

The linear specification problem is NOT unique to APC models. In fact, it appears to be the cause of scores constantly being recalibrated.



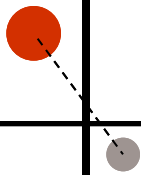
Counter-Adjustments to Lifecycle and Credit Risk





3. Fit the Score

- Using GLM and monthly performance data, use $F(a) + H(t)$ as a fixed offset.
- The score is estimated as
- `glm(Bad ~ 1 + offset(F+H) + factor1 + factor2 + ...)`
- At this point, the factors can be either origination or behavior variables without destabilizing the probability model.



Score Example

- “Offset” captures the population odds. The rest of the model is the idiosyncratic variation – a score.

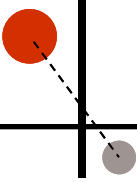
```
glm(formula = Bad ~ 1 + offset(offset) + Bureau.Score + log(LTV) +  
    Subcategory + Log.Dep.Bal + Term, family = binomial, ...)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.2726	-0.0276	-0.0133	-0.0042	4.7835

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	10.306961	1.367256	7.538	4.76e-14 ***
Bureau.Score	-0.012886	0.001830	-7.043	1.88e-12 ***
log(LTV)	1.203598	0.546832	2.201	0.0277 *
SubcategoryNew	0			
SubcategoryUsed	0.133842	0.312062	0.429	0.6680
Log.Dep.Bal	-0.918796	0.187975	-4.888	1.02e-06 ***
Term	-0.017266	0.008915	-1.937	0.0528 .



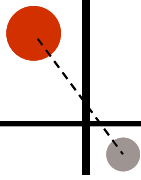
Outputs – The Score

- The glm-avt result is still a “score” if you exclude the offset term.
 - It can be scaled to match scores currently in use.
 - It will be more robust to changes in the economy – recalibrate much less often.
 - It can incorporate measured adverse selection for existing loans.
 - It can be built across both older and more recent data history to capture more consumer dynamics.

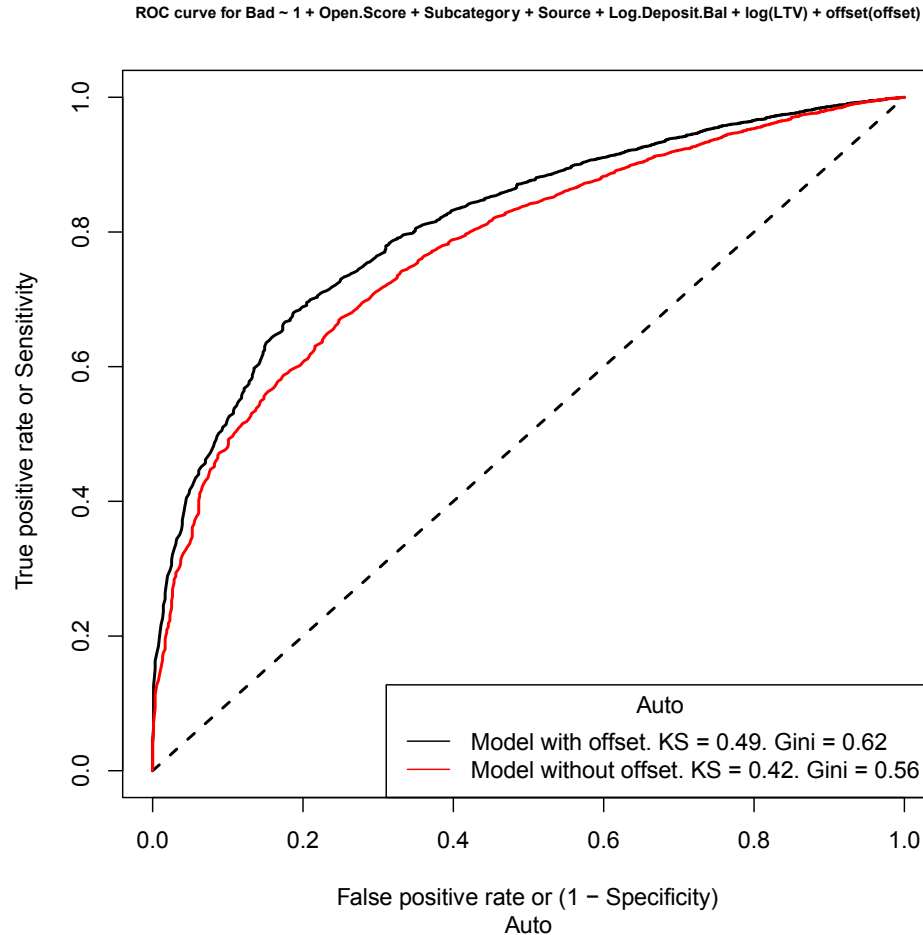


Outputs – The Probability

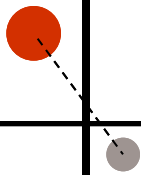
- p_i is the complete probability including the offset term to provide population odds over time.
 - It is conditional on age of the loan, “score”, and scenario for the environment.
 - It is available for each month, arbitrarily far into the future.
 - It can be aggregated over any desired time window to predict total probability.



Scoring with and without Offset

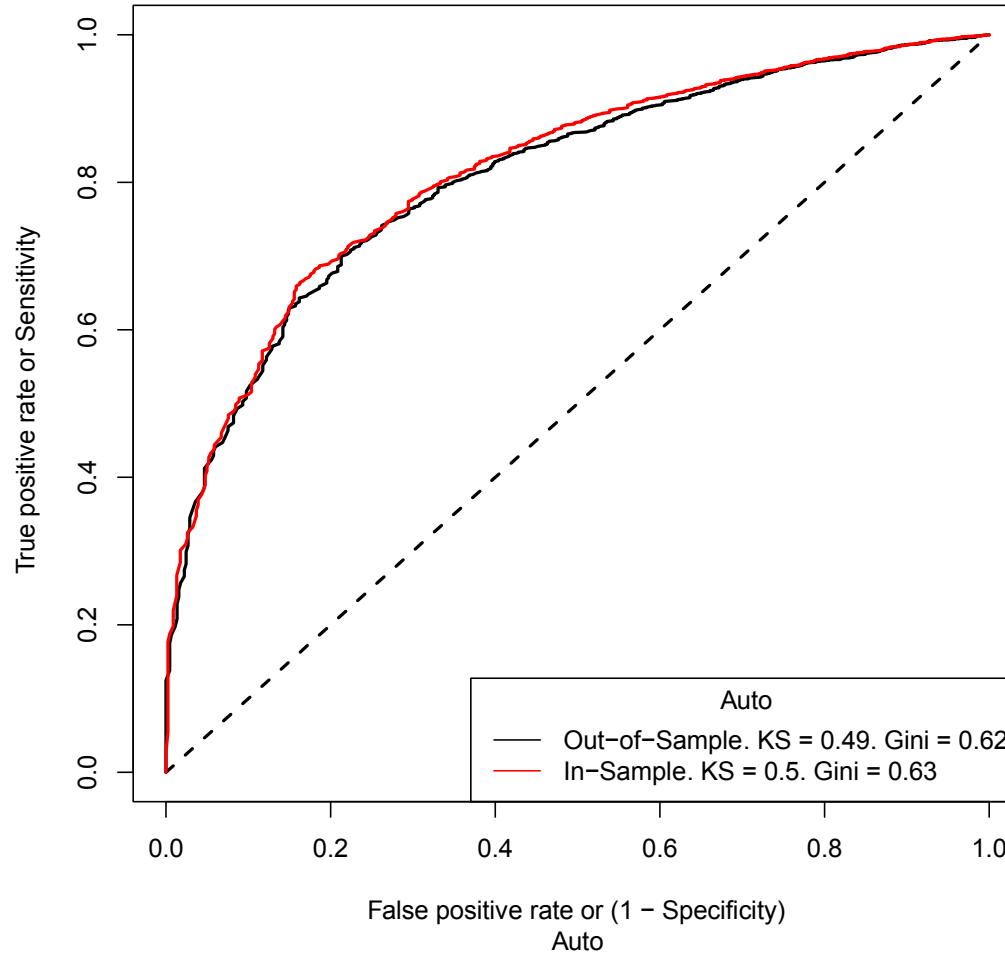


The scoring offset = $F(a) + H(t)$



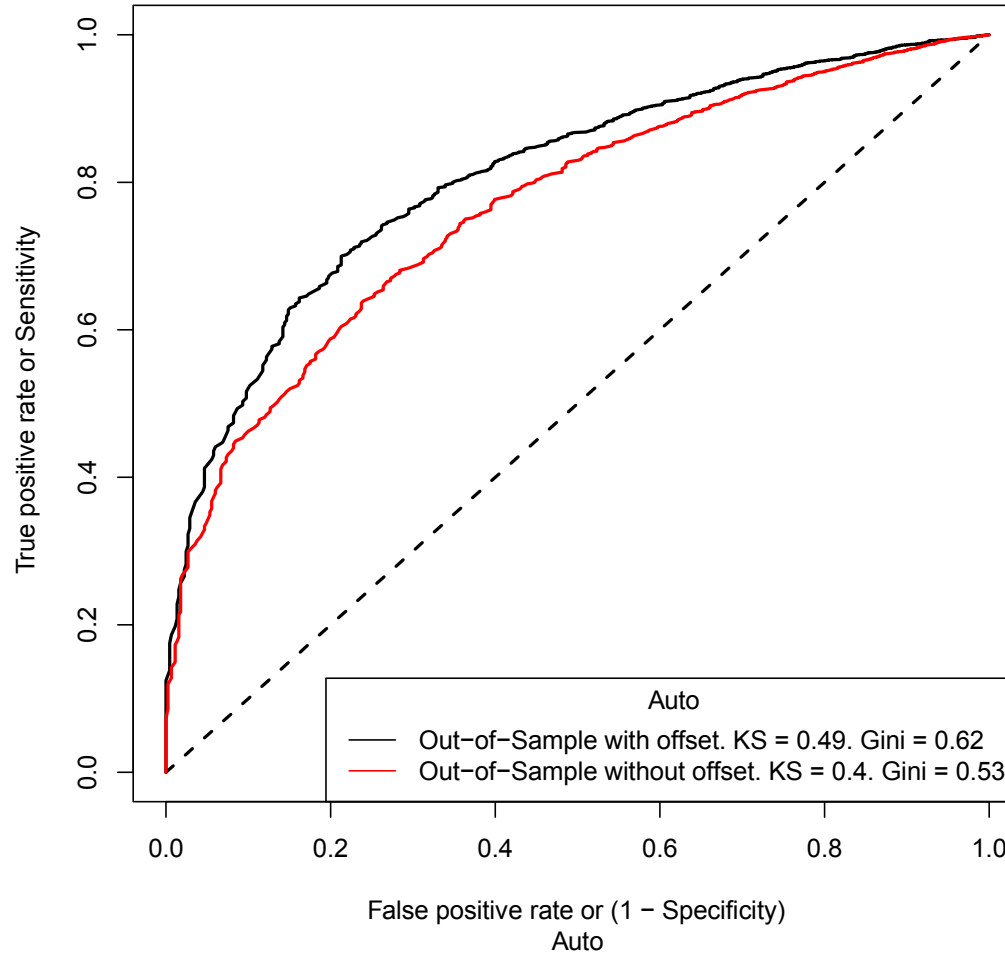
Out-of-Sample Validation

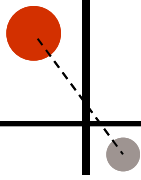
ROC curve for Bad ~ 1 + Open.Score + Subcategory + Source + Log.Deposit.Bal + log(LTV) + offset(offset)



Out-of-Sample Validation, with and without Offset

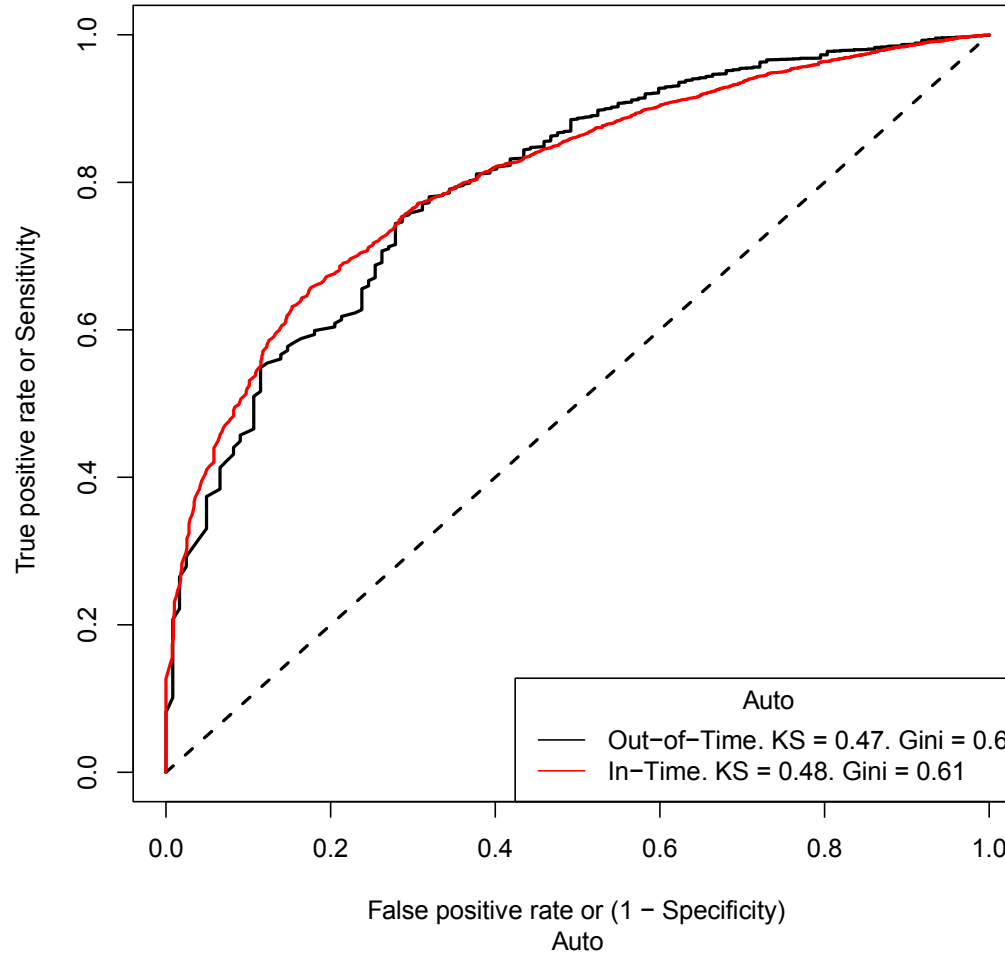
ROC curve for Bad ~ 1 + Open.Score + Subcategory + Source + Log.Deposit.Bal + log(LTV) + offset(offset)





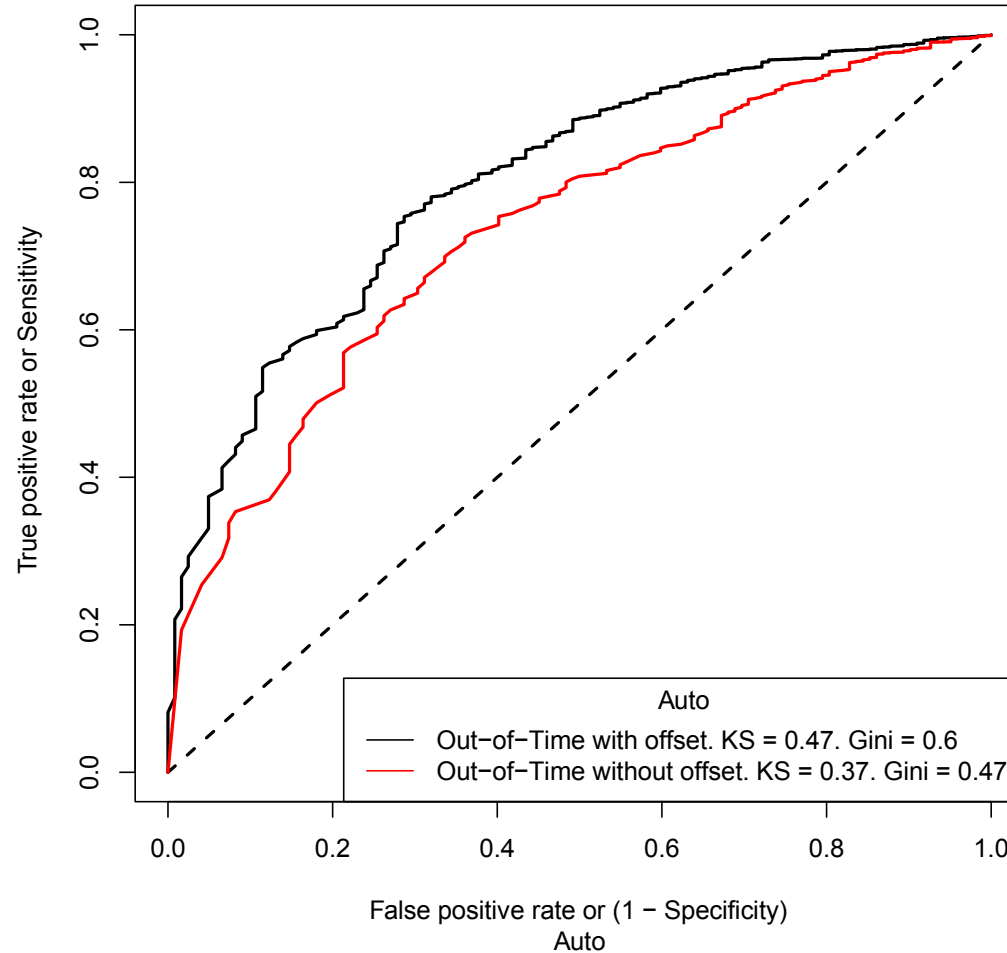
Out-of-Time Model Validation

ROC curve for Bad ~ 1 + Open.Score + Subcategory + Source + Log.Deposit.Bal + log(LTV) + offset(offset)



Out-of-Time Validation, with and without Offset

ROC curve for Bad ~ 1 + Open.Score + Subcategory + Source + Log.Deposit.Bal + log(LTV) + offset(offset)





Forecasting

- Use lifecycle and an environmental scenario to create the offset.
- The model predicts loan-level, monthly probabilities.
- Integrate over the product lifetime for pricing or a fixed window for account management.
- Also works for behavior scoring.



Stress Testing & Capital

- No additional modeling is required for stress testing.
- Insert an extreme scenario for the future $H(t)$ and aggregate the probabilities over the desired forecast horizon.
- Through the cycle PDs can be obtained the same way, by setting $H(t) = H_{TTC}$.
- No difference between stress testing and capital.



Contact Us

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