Loss Forecasting for Consumer Loan Portfolios

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CSCC IX, Edinburgh
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Objectives of Loss Forecasting

- **Analyze the past**
  - Impact of marketing campaigns
  - Impact of credit policies and collections strategies
  - Diagnostics for portfolio trends and deviations

- **Predict the future**
  - Predict delinquencies and charge-offs from newer vintages
  - Overall portfolio losses
  - Impact of changes in economic and industry environment

- **Planning**
  - Set aside economic loss reserves
  - Evaluate loss impact of new marketing and collections plans

- **Satisfy regulatory requirements**
  - Basel II
Data Requirements for Loss Forecasting

- Delinquency and charge-off history files
  - Account level details for 3-5 years
  - Segment level details for 10 years

- Account Management actions logs
  - Credit Policies
  - Collections strategies

- Account acquisition history
  - Marketing campaigns
  - Industry and economic climate at acquisition time

- Industry and economic history
  - Actions of competitors over time
  - Macro economic data over time
Forecasting Techniques

- Traditional/Unconditional methods
  - Net flow rates
  - Vintage loss curves
  - Score distributions

- Econometric/Conditional methods
  - Regression
  - Time series
  - Wavelets

- Simulation and Scenario based forecasting
  - Monte Carlo simulation
  - What-if scenario analysis
Net Flow Rates - Overview

- Examines rates at which accounts flow into each delinquency bucket and into charge-off.
- Movements into and between buckets are captured by *net flow rates* to the next bucket.
- Separate flow rates calculated for each line of business and segment.
- Average balances projected from preceding bucket in previous month.
- Bankruptcies and settlement charge-offs estimated based upon charge-offs per active account.
## Net Flow Rate - Example

4.99% of current accounts in Jan '02 become 30 days delinquent in Feb '02

<table>
<thead>
<tr>
<th>Month</th>
<th>Total</th>
<th>Active</th>
<th>0 Days</th>
<th>30 Days</th>
<th>0 to 30</th>
<th>60 Days</th>
<th>30 to 60</th>
<th>90 Days</th>
<th>60 to 90</th>
<th>120 Days</th>
<th>90 to 120</th>
<th>Charge-Offs</th>
<th>120 to Charg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan-02</td>
<td>5,000,000</td>
<td>3,223,096</td>
<td>2,708,576</td>
<td>1,380,106</td>
<td>135,704</td>
<td>6,259,2</td>
<td>20,993</td>
<td>15,504</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Feb-02</td>
<td>4,931,093</td>
<td>3,042,517</td>
<td>2,572,443</td>
<td>1,352,480</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Mar-02</td>
<td>4,904,921</td>
<td>3,113,894</td>
<td>2,540,610</td>
<td>1,499,077</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Apr-02</td>
<td>5,053,111</td>
<td>2,871,802</td>
<td>2,372,516</td>
<td>1,564,055</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>May-02</td>
<td>4,757,579</td>
<td>3,499,756</td>
<td>3,020,579</td>
<td>1,076,666</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Jun-02</td>
<td>4,797,436</td>
<td>2,705,767</td>
<td>2,319,788</td>
<td>1,595,211</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Jul-02</td>
<td>4,893,318</td>
<td>3,413,728</td>
<td>2,916,158</td>
<td>1,464,428</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Aug-02</td>
<td>4,873,484</td>
<td>2,995,243</td>
<td>2,565,683</td>
<td>918,433</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Sep-02</td>
<td>4,782,782</td>
<td>3,474,030</td>
<td>2,804,788</td>
<td>1,731,777</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Oct-02</td>
<td>4,988,121</td>
<td>3,365,931</td>
<td>2,999,460</td>
<td>1,183,388</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Nov-02</td>
<td>5,239,003</td>
<td>2,991,770</td>
<td>2,598,154</td>
<td>1,529,561</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
<tr>
<td>Dec-02</td>
<td>4,943,682</td>
<td>3,204,539</td>
<td>2,734,118</td>
<td>1,412,767</td>
<td>105,386</td>
<td>1,705,480</td>
<td>22,461</td>
<td>22,461</td>
<td>20,993</td>
<td>100.00%</td>
<td>20,993</td>
<td>100.00%</td>
<td>3,223,096</td>
</tr>
</tbody>
</table>

3,223,095 accounts roll into 12967 charge-offs with annualized charge-off rate of 4.8%
Net Flow Rate Example: Adjusting for Seasonality

<table>
<thead>
<tr>
<th>Month</th>
<th>Total</th>
<th>Active</th>
<th>0 Days</th>
<th>30 Days</th>
<th>0 to 30</th>
<th>60 Days</th>
<th>30 to 60</th>
<th>90 Days</th>
<th>60 to 90</th>
<th>120 Days</th>
<th>90 to 120</th>
<th>Charge</th>
<th>120 to Charg</th>
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</thead>
<tbody>
<tr>
<td>Jan-02</td>
<td>5,000,000</td>
<td>3,223,096</td>
<td>2708576</td>
<td>138010</td>
<td>62592</td>
<td>20993</td>
<td>15504</td>
<td>20304</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feb-02</td>
<td>4953109</td>
<td>3,042,517</td>
<td>2572243</td>
<td>135248</td>
<td>53557</td>
<td>38.81%</td>
<td>22461</td>
<td>35.88%</td>
<td>20993</td>
<td>100.00%</td>
<td>15504</td>
<td>100.00%</td>
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<tr>
<td>Mar-02</td>
<td>4904991</td>
<td>3,113,894</td>
<td>2540610</td>
<td>149907</td>
<td>50032</td>
<td>36.99%</td>
<td>20013</td>
<td>37.37%</td>
<td>20384</td>
<td>90.75%</td>
<td>10391</td>
<td>49.50%</td>
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<td>5053111</td>
<td>2,871,802</td>
<td>2372516</td>
<td>156405</td>
<td>32108</td>
<td>21.42%</td>
<td>15676</td>
<td>31.33%</td>
<td>12809</td>
<td>64.00%</td>
<td>16991</td>
<td>83.35%</td>
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<tr>
<td>May-02</td>
<td>4757579</td>
<td>3,499,756</td>
<td>3020579</td>
<td>107666</td>
<td>49620</td>
<td>31.73%</td>
<td>30997</td>
<td>96.54%</td>
<td>15676</td>
<td>100.00%</td>
<td>12029</td>
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<tr>
<td>Jun-02</td>
<td>4797436</td>
<td>2,705,767</td>
<td>2319788</td>
<td>159521</td>
<td>35672</td>
<td>33.13%</td>
<td>23269</td>
<td>46.89%</td>
<td>10495</td>
<td>33.86%</td>
<td>12967</td>
<td>82.72%</td>
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<tr>
<td>Jul-02</td>
<td>4893318</td>
<td>3,413,728</td>
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<td>2,995,243</td>
<td>2565833</td>
<td>91843</td>
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<td>26008</td>
<td>53.05%</td>
<td>21039</td>
<td>100.00%</td>
<td>15735</td>
<td>97.76%</td>
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<tr>
<td>Sep-02</td>
<td>4782782</td>
<td>3,474,030</td>
<td>2804788</td>
<td>173177</td>
<td>44291</td>
<td>48.22%</td>
<td>33136</td>
<td>69.02%</td>
<td>21253</td>
<td>81.44%</td>
<td>14616</td>
<td>69.47%</td>
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<td>Oct-02</td>
<td>4988121</td>
<td>3,365,931</td>
<td>2999460</td>
<td>118388</td>
<td>39906</td>
<td>22.47%</td>
<td>23146</td>
<td>52.26%</td>
<td>15841</td>
<td>47.81%</td>
<td>14074</td>
<td>66.22%</td>
<td></td>
</tr>
<tr>
<td>Nov-02</td>
<td>5239003</td>
<td>2,991,770</td>
<td>2584154</td>
<td>152951</td>
<td>46657</td>
<td>39.41%</td>
<td>17197</td>
<td>44.20%</td>
<td>14658</td>
<td>63.33%</td>
<td>15841</td>
<td>100.00%</td>
<td></td>
</tr>
<tr>
<td>Dec-02</td>
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<td>2734118</td>
<td>141276</td>
<td>48221</td>
<td>31.53%</td>
<td>23593</td>
<td>50.57%</td>
<td>12658</td>
<td>73.61%</td>
<td>14658</td>
<td>100.00%</td>
<td></td>
</tr>
</tbody>
</table>

Build moving averages/exponential smoothing model for each data series to adjust for seasonality

No attempt to model macro-economic, industry or policy variables
Vintage Curves - Overview

- Based upon account charge-off rate over time per original booked accounts
- Tracks losses per month over the life of vintages
- Critical assumption: Recent vintages will mature along the same path as old vintages
- Percentage of lifetime losses already occurred calculated for older vintages
- Separate curves made for each line of business and segment
Vintage Curves - Example

- Vintage curves stable enough to be used in long term forecasts
- New cohorts matched with old for characteristics, vintage curve of matching cohort used for new cohort forecast
Score Distributions - Overview

- Use percentage of actual losses by score interval for very mature vintages, or
- Use percentage of actual losses by score interval for a specific time period, e.g., 6 or 12 months
- Use acquisition score for new vintages, behavior score for mature vintages
## Score Distributions - Example

<table>
<thead>
<tr>
<th>Acquisition Score</th>
<th>Current to Charge-off</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 540</td>
<td>9.60%</td>
</tr>
<tr>
<td>560</td>
<td>8.00%</td>
</tr>
<tr>
<td>580</td>
<td>7.30%</td>
</tr>
<tr>
<td>600</td>
<td>6.20%</td>
</tr>
<tr>
<td>620</td>
<td>5.60%</td>
</tr>
<tr>
<td>640</td>
<td>4.80%</td>
</tr>
<tr>
<td>680</td>
<td>3.90%</td>
</tr>
<tr>
<td>700</td>
<td>3.10%</td>
</tr>
<tr>
<td>720</td>
<td>2.00%</td>
</tr>
<tr>
<td>740</td>
<td>1.50%</td>
</tr>
<tr>
<td>760</td>
<td>1.00%</td>
</tr>
<tr>
<td>&gt; 780</td>
<td>0.50%</td>
</tr>
</tbody>
</table>
Impact of information gathered at time of solicitation decreases as the cohort matures
Comparison of Traditional Methods

- **Net flow rate**
  - Accurate in the short term (0-6 months)
  - More accurate for revolving and closed-end loans
  - Offers high degree of detail, good for diagnostics
  - Delinquency buckets dependent upon collections strategies

- **Vintage curves**
  - Good long term accuracy for closed-end loans
  - Can be inaccurate for revolving loans due to impact of policies such as balance transfers and teaser rates
  - Not as granular as net flow rates

- **Score distributions**
  - Most accurate for brand new vintages
  - Effective time period depends upon observation period used in developing score
  - Most useful for current to charge-off prediction, not as useful for delinquency buckets or monthly predictions
Integration of Different Traditional Methods

- Ad hoc integration
  - Assign weights to different methods based upon experience (e.g., 0.3333 for each of three methods)
  - Change weights over time, e.g., more weight to scores in 0-3 months, more weight to flow rates in 4-12 months, more weights to vintage thereafter

- Segmented integration example
  - Current to 30 days delq., use flow rate by acquisition score segment and vintage
  - Use flow rate by vintage for all other buckets
  - Use scores for very small portfolios as well as brand new vintages
Traditional/Unconditional Methods - Critique

- If future is like the past, unconditional models will be accurate, i.e., forecast error will be random.
- If future is not like past, conditional models incorporating information about changes in conditions more likely to create accurate forecasts.
- Ad hoc adjustments to account for expected changes may not be sufficient.
- Unconditional models not well suited for simulation/scenario analysis.
Improving Accuracy of Loss Forecasting Systems

- Use conditional models!
  - Techniques include regression, time series analysis, and wavelets
  - Increased data requirements might be an issue

- Model roll-rate time series as a function of macro-economic, industry, bank policy, and portfolio-specific variables

- Modeling complicated because some of the factors are time-based (e.g., economic environment) whereas other factors are age-based (e.g., solicitation information)
Bank policies change over time and impact delinquencies and charge-offs.

- As delinquencies went up
- More accounts were re-aged
- And application cut-offs tightened
Long Term Forecasts: Macro-economic Variables

- Macro-economic variables also impact delinquencies and charge-offs
## Conditional Loss Forecasting Models

### Sample Results

<table>
<thead>
<tr>
<th>Models</th>
<th>Original Times Series</th>
<th>Wavelets Decomposition (Trend + Scales)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>12 month total loss prediction error (%)</td>
<td>12 month mean abs prediction error (%)</td>
</tr>
<tr>
<td>Without Economic Variables</td>
<td>79.41</td>
<td>2.42</td>
</tr>
<tr>
<td>Constant forecast from last 6m actual</td>
<td>36.12</td>
<td>1.41</td>
</tr>
<tr>
<td>TSFS</td>
<td>60.12</td>
<td>0.71</td>
</tr>
<tr>
<td>ARIMA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>With Economic Variables</td>
<td>56.8</td>
<td>0.59</td>
</tr>
<tr>
<td>VARMAX</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multiple Step Regression</td>
<td>63.6</td>
<td>0.81</td>
</tr>
</tbody>
</table>

Lack of long time series data impeded efforts to build anything but simple models.
Improving Transparency of Loss Forecasting System

- Run Monte-Carlo simulations to get:
  - Estimates of expected as well as unexpected losses
  - Determine key loss drivers
  - Evaluate impact of future macro-economic as well as industry scenarios on losses
  - Evaluate impact of changes in bank policies on future losses
Simulating Loss Distribution

![Graph showing simulated loss distribution with areas labeled as Expected Losses and Unexpected Losses.](image)
SAS Forecasting Products

- Heavy user involvement
- Great breadth and depth of modeling techniques, no automation
- No GUI – batch
- High valued items (‘A’ class items)
- Small amount of series

- Medium user involvement
- Automatic + modeling
- GUI – not batch
- Medium valued items (‘B’ class items)
- Medium amount of series
SAS/TSFS Capabilities

- Creates and saves forecasting projects
- Interactive time series exploration
- Automatic forecasting (not batch)
  - 42 canned time series models
  - “Infinite” model list
- Modeling environment for experienced forecasters
  - ARIMA, smoothing models, regressors, etc.
SAS/TSFS GUI

Solutions → Analysis → Time Series Forecasting System
SAS/ETS Capabilities

- Time series data management
- Access engines for economic and financial databases
- Econometric analysis
- Modeling and simulation
- Time series forecasting
- Seasonal adjustment of time series data
- Interactive forecasting user interface
SAS/ETS: Vector Time Series

- Often, economic or financial variables are not only contemporaneously correlated to each other, they are also correlated to each other's past values.
- Analyzing, modeling, and forecasting these variables independently can lead to poor results.
Univariate Time Series Model - Example

Model and forecast each univariate time series associated with each delinquency bucket INDEPENDENTLY.

\[ y_{it} = c_i + \phi y_{it-1} + \varepsilon_{it} \]

where,

c_i is the constant term,
\( \phi \) is the first-order autoregressive parameter
\( \varepsilon_{it} \) is the white noise disturbance term
Vector Time Series Model - Example

- Model and forecast the univariate time series associated with each delinquency bucket JOINTLY.

\[ Y_t = C + \Phi Y_{t-1} + E_t \]

where,
- \( C \) is the Nx1 constant vector
- \( \Phi \) is the NxN first-order autoregressive parameter matrix
- \( E_t \) is the Nx1 white noise disturbance vector
SAS/ETS: The UCM Procedure

UCM = Unobserved Component Models

- Also known as Structural Time Series Models
- Decomposes series into components
  - Trend component
  - Seasonality
  - Cycles
  - Random error
- Forecasts each component
- Automatically deals with non-stationarity
- Very useful for forecasting purposes
The UCM Procedure Example: U.S. Long-Term Unemployment

- Series = Trend + Cycle + Random Error
- Trend: Locally Linear Stochastic Trend
- Cycle: A Stochastic Cycle with Fixed Period but Slowly Varying Amplitude and Phase
- Random Error: Simple Independent Normal Errors
- For Model Validation the Last 18 Months of Data are Withheld from the Modeling Process
UCM Procedure – Trend Component

Trend Component
Smoothed Estimate

Long Term Unemployment


Actual  Start of multi-step forecasts
UCM Procedure – Cycle Component
(Estimated Period = Approx 3 Years)
Wavelet Analysis

Definition:
- Wavelet Analysis breaks up of a signal into Shifted and Scaled versions of the mother wavelet

Advantages (compared to frequency-based analysis):
- Scale-based analysis is less sensitive to noise
- Local analysis catches the sharp changes of signal
- Multi-scale resolution reveals all aspects such as trends, breakdown points, discontinuities in higher derivatives, and self-similarity.

Uses for loss forecasting
- Non-linear decomposition and forecasting
- Noise filtering
- Identifying unexpected events
Noise Filtering with Wavelets

- Takes the wavelet transform
- Filters in wavelet domain at each scale
  - The wavelet coefficients are weakly correlated both along and across scales
  - The signal in wavelet domain has the variance progression property
- Reconstructs the signal
  - No inverse wavelet transform is needed

\[
x(t) = s(t) + \varepsilon(t)
\]

\[
X^m_n = S^m_n + \varepsilon^m_n
\]

\[
\hat{S}^m_n = E[S^m_n | X^m_n] = F(m, \theta)X^m_n
\]

\[
\hat{s}(t) = \sum_{m,n} F(m, \theta)X^m_n \psi^m_n(t)
\]

\[
x(t) = \sum_{m=1}^{M} W_m(t) + f_M(t)
\]
Wavelet Noise Filtering Example

- Example: Daily crude oil spot price from 1/2/1986 to 6/3/2003

- Observed
- Estimated
- Separated
Modeling Using Proprietary Neuro-Wavelet Technique
Wavelet: Identifying Unexpected Events

- 12/18/2000 – 1/4/2001

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SAS Enterprise Intelligence
Other SAS Tools for a Loss Forecasting System

Automated Data Collection
CLF Data Staging
DW / DM
ETLQ Intelligent Storage

User Workspace Infrastructure
Analytic Intelligence Business Intelligence
Information Delivery Portal

Automated Report Distribution
Forecasts
Reports
Ad-hoc

Automated Forecast
Last Month plus New Month Accruals

Data Sources

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Q & A

- Thank you for the opportunity to present