

# Marginal Chi<sup>2</sup> Analysis:

## *Beyond Goodness of Fit for Logistic Regression Models*

**Quantitative Financial Risk Management Centre**

**Conference on Risk Management  
in the Retail Financial Services Sector**

**London – 22-23 January 2009**

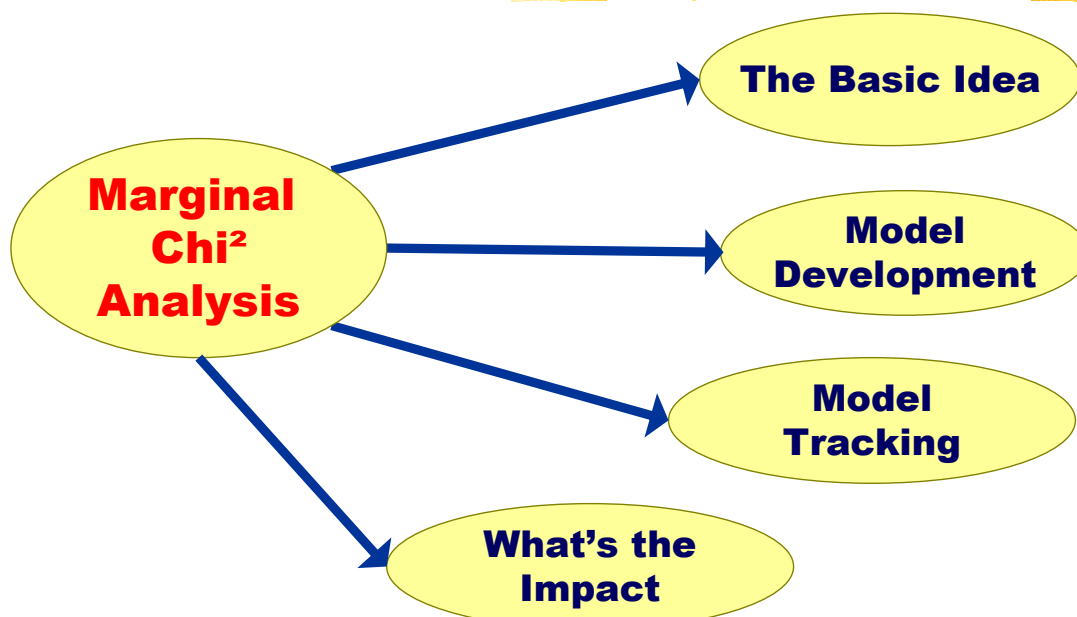
Gerard.Scallan  
@scoreplus.com



→ data → information → profit

QFRMC Conference 23/01/2009 - © ScorePlus SARL 2009

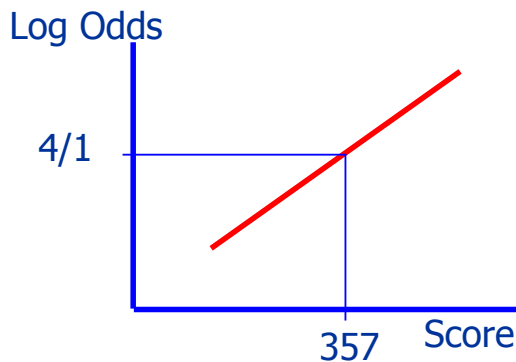
## Structure of Presentation



# Logistic Regression:

## *Two basic ideas*

### Score = Log (Odds)



### Actual = Expected

- ◆ For each categorical variable in model:
  - ◆ e.g. residential status
- ◆ Actual Goods in Attribute = Expected Goods in Attribute
- ◆ Actual Bads in Attribute = Expected Bads in Attribute
- ◆ Direct consequence of maximum likelihood equations
- ◆ Analogous result on averages for continuous predictors

**Model correctly estimates "average" risk for each group**

## Actual = Expected Equations

### *... equivalent to Maximum Likelihood*

Problem : estimate scorecard  $\beta$  from sample of Goods ( $G$ ) and Bads ( $B$ )

$$\text{For case } i : \Pr_{\beta}(i \in G) = \frac{e^{x_i' \beta}}{1 + e^{x_i' \beta}} \quad \Pr_{\beta}(i \in B) = \frac{1}{1 + e^{x_i' \beta}}$$

$$\text{Likelihood Function : } L(\beta) = \prod_{i \in G} \frac{e^{x_i' \beta}}{1 + e^{x_i' \beta}} \times \prod_{i \in B} \frac{1}{1 + e^{x_i' \beta}}$$

$$\ln L(\beta) = \sum_{i \in G} x_i' \beta - \sum_{i \in G \cup B} \ln(1 + e^{x_i' \beta})$$

Maximise by setting partial derivatives w.r.t. each component  $j$  of  $\beta$  to zero :

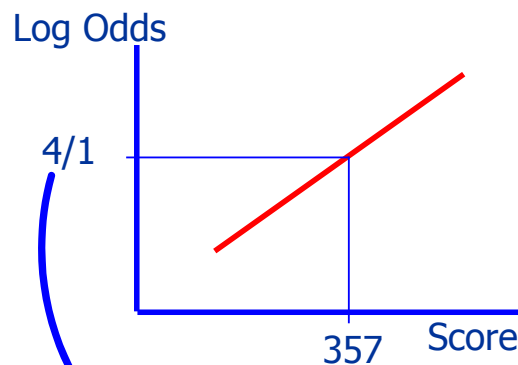
$$\frac{\partial \ln L(\beta)}{\partial \beta_j} = \sum_{i \in G} x_{ij} - \sum_{i \in G \cup B} \frac{e^{x_i' \beta} x_{ij}}{1 + e^{x_i' \beta}} = \sum_{i \in G} x_{ij} - \sum_{i \in G \cup B} x_{ij} \Pr_{\beta}(i \in G) = 0$$

Let  $x_{ij} = 1$  if  $i$  is in category  $A_j$ ,  $x_{ij} = 0$  otherwise :

$$\|A_j \cap G\| = \sum_{i \in A} \Pr_{\beta}(i \in G)$$

**Actual Goods = Expected Goods**

# What is "Expected"?



$$\begin{aligned}\Pr(\text{Good}) &= 0.8 \\ \Pr(\text{Bad}) &= 0.2\end{aligned}$$

**Model implies "expected" outcome for each sample point**

## Characteristic in model (Categorical variables)

Subpopulation: High Risk Population - Model Build Sample  
Characteristic: C007 CTO Current Credit Turnover

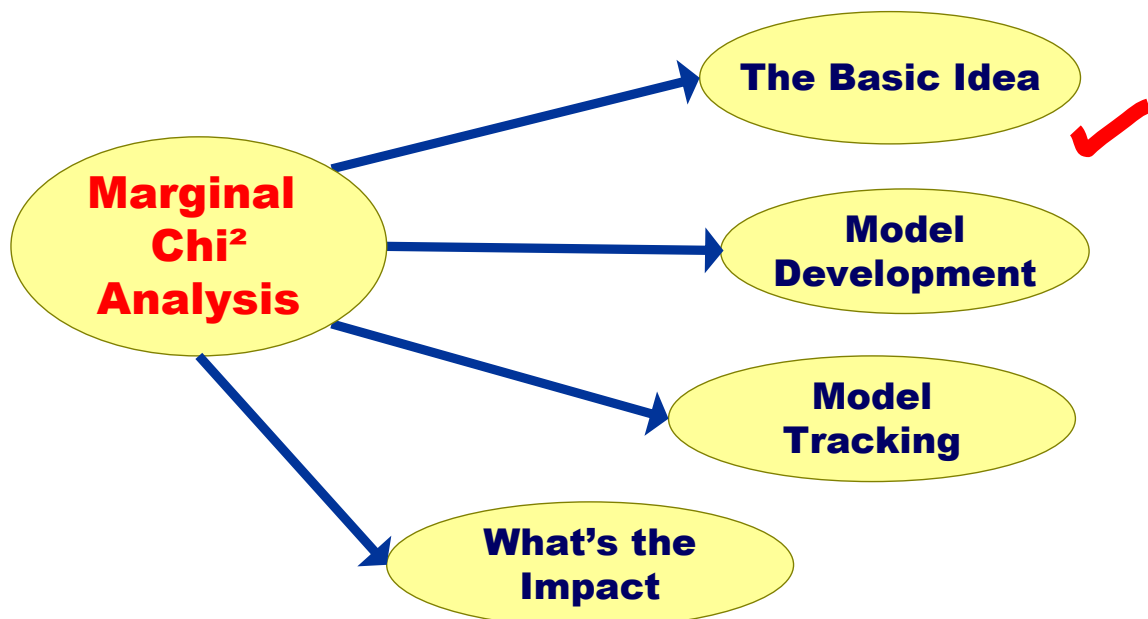
| Attribute Description | ACTUALS     |            |             |                    | EXPECTED (by score) |            |             |                    |
|-----------------------|-------------|------------|-------------|--------------------|---------------------|------------|-------------|--------------------|
|                       | Goods Count | Bads Count | Total Count | Weight of Evidence | Goods Count         | Bads Count | Total Count | Weight of Evidence |
| 1. <= 500             | 761         | 415        | 1176        | -1.503             | 761.0               | 415.0      | 1176.0      | -1.503             |
| 2. <= 1500            | 197         | 57         | 254         | -0.875             | 197.0               | 57.0       | 254.0       | -0.875             |
| 3. <= 2500            | 148         | 35         | 183         | -0.678             | 148.0               | 35.0       | 183.0       | -0.678             |
| 4. <= 3000            | 99          | 23         | 122         | -0.666             | 99.0                | 23.0       | 122.0       | -0.666             |
| 5. <= 4000            | 253         | 46         | 299         | -0.413             | 253.0               | 46.0       | 299.0       | -0.413             |
| 6. <= 5000            | 369         | 52         | 421         | -0.157             | 369.0               | 52.0       | 421.0       | -0.157             |
| 7. > 5000             | 5896        | 309        | 6205        | 0.838              | 5896.0              | 309.0      | 6205.0      | 0.838              |
| Total (Valid)         | 7723        | 937        | 8660        |                    | 7723.0              | 937.0      | 8660.0      |                    |

|                             |                |                             |                |
|-----------------------------|----------------|-----------------------------|----------------|
| Information value:          | 0.940          | Information value:          | 0.940          |
| Gini Coefficient            | 47.7%          | Gini Coefficient            |                |
| Likelihood Ratio Chi² (G²): | 814.210 6 D.F. | Likelihood Ratio Chi² (G²): | 814.210 6 D.F. |
| Chi Square Significance:    | 0.00000%       | Chi Square Significance:    | 0.00000%       |

**Exact Equality: maximum likelihood equations**

# Structure of Presentation



## Marginal Chi²: *Characteristic not (yet) in model*

- ◆ Null Hypothesis: Existing score accurately estimates probabilities
  - ◆ Probabilities generate "expected" values in each cell

| Debit<br>Turnover | OBSERVED |        |       | EXPECTED |       |         |             |
|-------------------|----------|--------|-------|----------|-------|---------|-------------|
|                   | Goods    | Bads   | Total | Goods    | Bads  | Total   |             |
| ≤ 1000            | 436      | 174    | 610   | 487.7    | 122.3 | 610     | overscored  |
| 1000 ≤ 2000       | 178      | 38     | 216   | 184.6    | 31.4  | 216     | overscored  |
| 2000 ≤ 2500       | 84       | 17     | 101   | 86.2     | 14.8  | 101     | overscored  |
| 2500 ≤ 3500       | 263      | 46     | 309   | 263.1    | 45.9  | 309     | ok          |
| > 3500            | 6240     | 618    | 6858  | 6179.4   | 678.6 | 6858    | underscored |
| Total             | 7201     | 893    | 8094  | 7201     | 893   | 8094    |             |
|                   |          | Chi² = | 33.06 | D.F. =   | 4     | p-value | 0.00012%    |

- ◆ Calculated on model build sample:
  - ◆ Intercept term in model guarantees actual = expected for total sample
- ◆ Use Log-Likelihood Chi² - a matter of taste!

**Observed pattern not explained by model estimates  
=> score is not a sufficient statistic for risk**

# Chi<sup>2</sup> Measure - Pros and Cons

## Pros

- ◆ Identify candidates for entry to model
- ◆ For many potential predictors, expected converges to actual rapidly
  - ◆ As terms added to model
  - ◆ Indicates common information content
  - ◆ Gives understanding of collinearity structure
- ◆ Highlights "incremental" information

## Cons

- ◆ Lots of very significant misfits
- ◆ Chi<sup>2</sup> measures certainty – not distance
  - ◆ 0.0000009% vs. 0.0000007% meaningless
- ◆ Ambiguity in degrees of freedom
  - ◆ Classed characteristics
- ◆ Chi<sup>2</sup> statistic proportional to sample size
  - ◆ Hinders learning across samples
- ◆ Beware of false positives!

**Right idea – wrong packaging**

# Marginal Information and Delta Scores

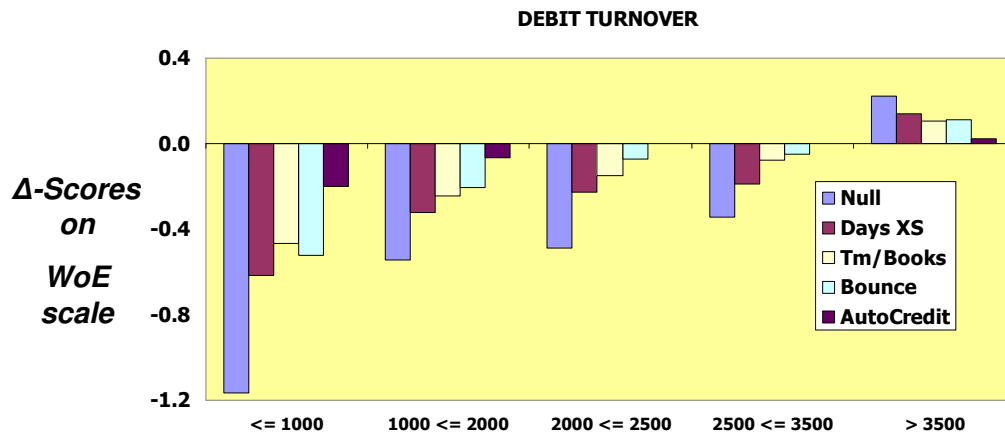
| Debit Turnover                                     | OBSERVED |      |       | EXPECTED |       |       | Δ-score |
|--|----------|------|-------|----------|-------|-------|---------|
|  | Goods    | Bads | WoE   | Goods    | Bads  | WoE   |         |
| ≤ 1000   | 436      | 174  | -1.17 | 487.7    | 122.3 | -0.70 | -0.46   |
| 1000 ≤ 2000  | 178      | 38   | -0.54 | 184.6    | 31.4  | -0.32 | -0.23   |
| 2000 ≤ 2500  | 84       | 17   | -0.49 | 86.2     | 14.8  | -0.33 | -0.16   |
| 2500 ≤ 3500  | 263      | 46   | -0.34 | 263.1    | 45.9  | -0.34 | 0.00    |
| > 3500   | 6240     | 618  | 0.22  | 6179.4   | 678.6 | 0.12  | 0.10    |
| Total  | 7201     | 893  | 0.00  | 7201     | 893   | 0.00  | 0.00    |
| Chi <sup>2</sup> = 33.06 D.F. = 4 p-value 0.00012% |          |      |       |          |       |       |         |
| Marginal Information Value 0.086                   |          |      |       |          |       |       |         |

- ◆ Weight of Evidence (WoE) = log (Attribute Odds) – log (Population Odds)
  - ◆ One-dimensional score coefficients
- ◆ Delta Score = Observed WoE – Expected WoE
  - ◆ **Approximation** to score coefficients needed to line up expected with observed
- ◆ Marginal Information Value = Avg<sub>Good</sub>(Delta Score) - Avg<sub>Bad</sub>(Delta Score)
  - ◆ Similar to Kullback-Liebler Information Value
  - ◆ Increased spread between average score of goods and bads
  - ◆ ... if this characteristic brought into model

# Measuring Collinearity

## Overlaps in predictive power

- Most information is not unique to a single characteristic
- Delta scores reduce in magnitude as "correlated" variables enter model

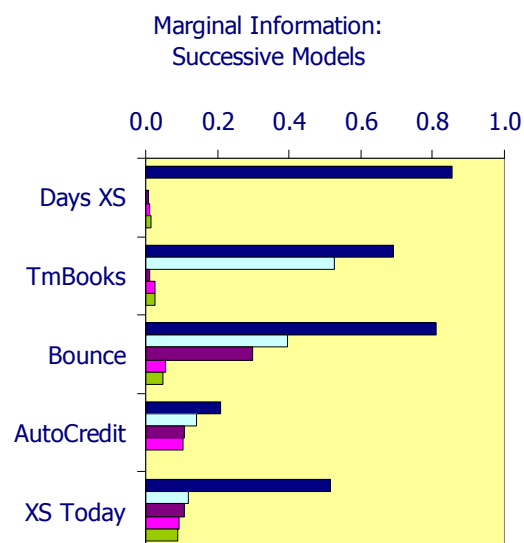


**Small Delta Scores => Information already covered by other characteristics in model**

# Selection of Model Characteristics

## Marginal IV

- Marginal IV is best indicator of potential contribution to model
- Choose the largest Marginal IV
- Provided "significant" Marginal Chi<sup>2</sup>
  - Problem with degrees of freedom
- Better approach than Stepwise
- Negative Marginal IVs indicate possible over-fitting
- Rule of Thumb:
  - $-.020 < \text{MIV} < .020$

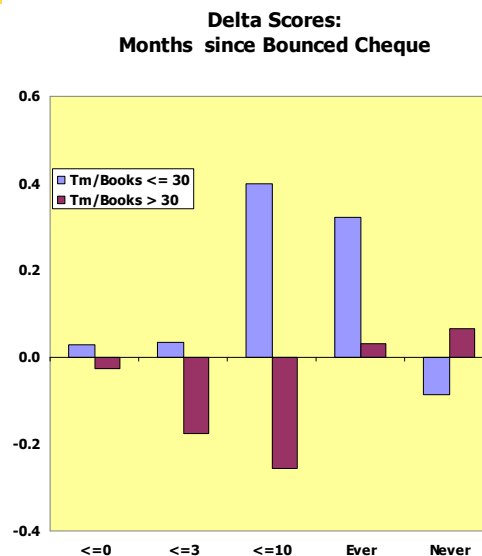


**Zero Marginal Information = Sufficient Statistic**

# Model Segmentation

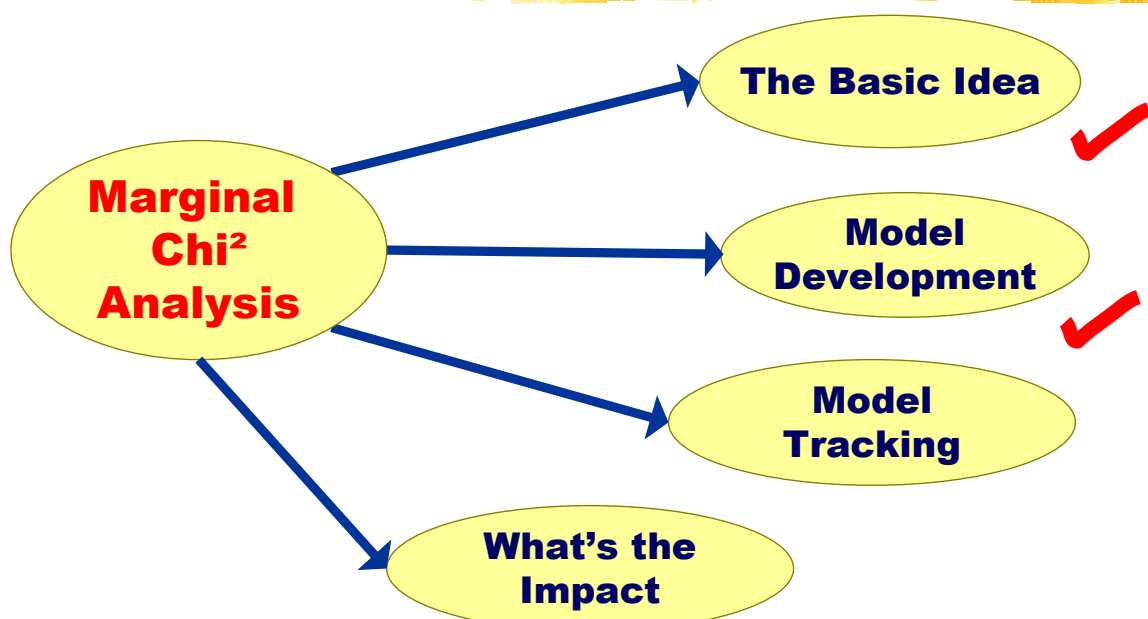
## Testing for Interactions

- ◆ Characteristic interactions
  - => Multiple models
    - ◆ e.g. Delinquency - Time on books
- ◆ Test for Actual = Expected on each subpopulation
  - ◆ For each predictive characteristic
  - ◆ Enables systematic screening for interactions
- ◆ Small samples => Statistics matter!
- ◆ Shows many splits unnecessary



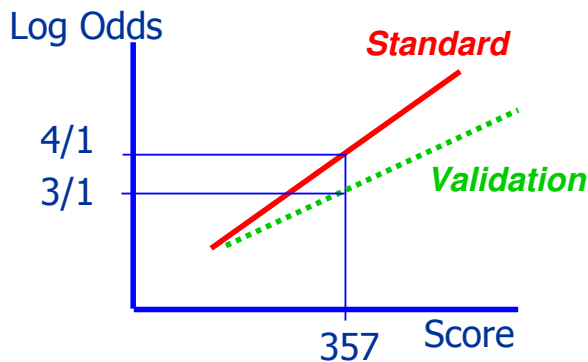
**Clear conceptual framework (and algorithm)  
for tough problem**

## Structure of Presentation



# Tracking Approach (and model validation!)

## Score = Log (Odds)



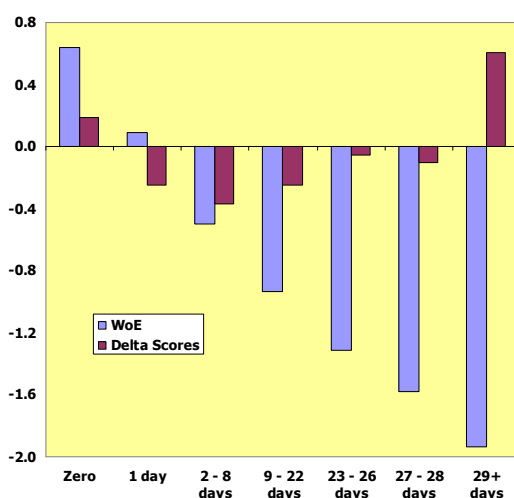
## Validation Process

- ◆ Key business decisions based on assumed score-risk relationship
  - ◆ Basis for strategies
  - ◆ Requires management assumptions on PIT parameters
- ◆ Fit logistic regression on validation population
  - ◆ Evaluates overall performance of model
  - ◆ Ensures Actual = Expected for total population
- ◆ Starting point for Marginal Chi<sup>2</sup> analysis

**Marginal Chi<sup>2</sup> reports should be part of regular monitoring**

# Change in Behaviour? Example of tracking analysis

Days in Excess This Month



- ◆ Clear WoE pattern
- ◆ IV: 0.62    Marginal IV: 0.07
  - ◆ But some negative contributions
- ◆ The Δ-scores show that scorecard "exaggerates"
  - ◆ Worst not as bad as scores suggest
- ◆ Why? Change in treatment of Excess?
- ◆ Zero excess (2/3 of population) is under-rated

**Use statistics to tell the business story**



# Assessing Branch Performance

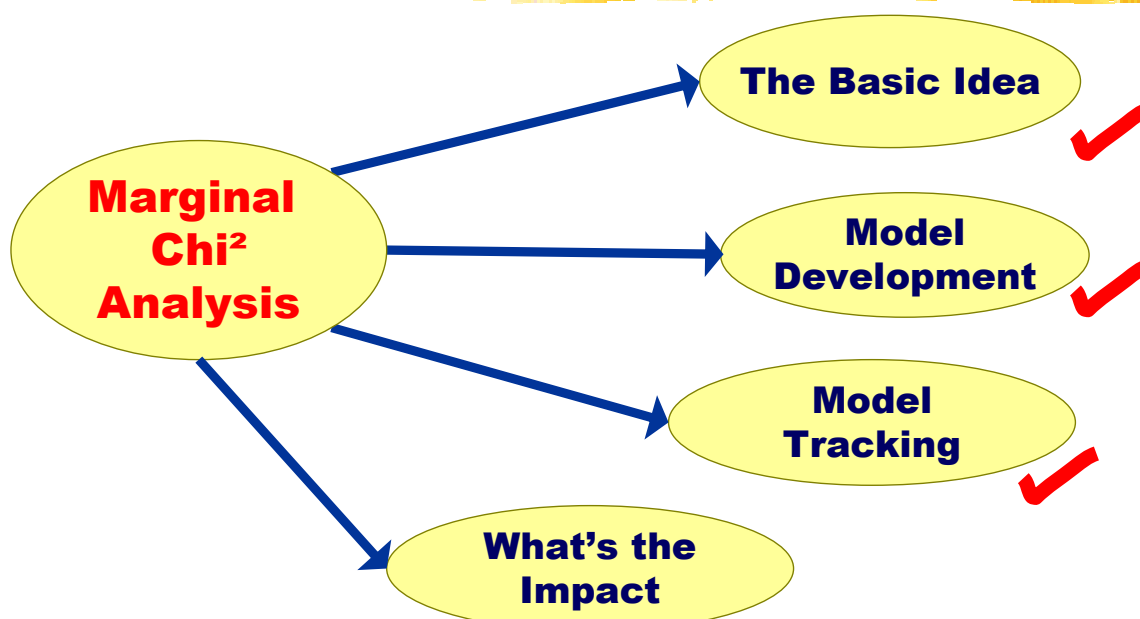
## *Adding business value*

| ACCOUNT OPENINGS 2008/Q2 |              |            |             |             |          |
|--------------------------|--------------|------------|-------------|-------------|----------|
| Store                    | Default Rate |            |             | Performance |          |
|                          | Budget       | At Opening | at 9 months | Absolute    | Relative |
| Paris                    | 3.5%         | 3.7%       | 3.9%        | Good        | Poor     |
| Lille                    | 5.0%         | 5.2%       | 4.8%        | Poor        | Good     |
| Lyon                     | 4.0%         | 3.9%       | 3.6%        | Good        | Good     |
| Marseille                | 4.8%         | 5.0%       | 5.3%        | Poor        | Poor     |
| Total                    | 4.1%         | 4.2%       | 4.2%        |             |          |

- ◆ "At opening" figures derived from scores on account opening time
  - ◆ Profile of applicants different from budget expectations
- ◆ Isolate departures from expectations
  - ◆ Take account of differing potential
- ◆ Can be extended to policy rules, marketing campaigns, collections strategies, ...

**The power of sufficient statistics ...**

## Structure of Presentation



# Basel: Litmus test for rating systems

## Basel Requirements

- ◆ Banks must use "all relevant and material information in assigning ratings" (Basel Accord, para. 411)
- ◆ Validation must show outcomes are in line with model expectations
- ◆ Management must show understanding of rating systems

## Marginal Chi<sup>2</sup> Approach

- ◆ ... allows rigorous verification that rating systems are "sufficient statistics"
- ◆ ... identifies any departures from model predictions
  - ◆ ... and suggests fixes
- ◆ ... provides understandable interpretation of ratings:
  - ◆ Actual = Expected

**Use Basel infrastructure to improve business decisions**

# The Credit Crunch ... and Marginal Chi<sup>2</sup>

## Principles

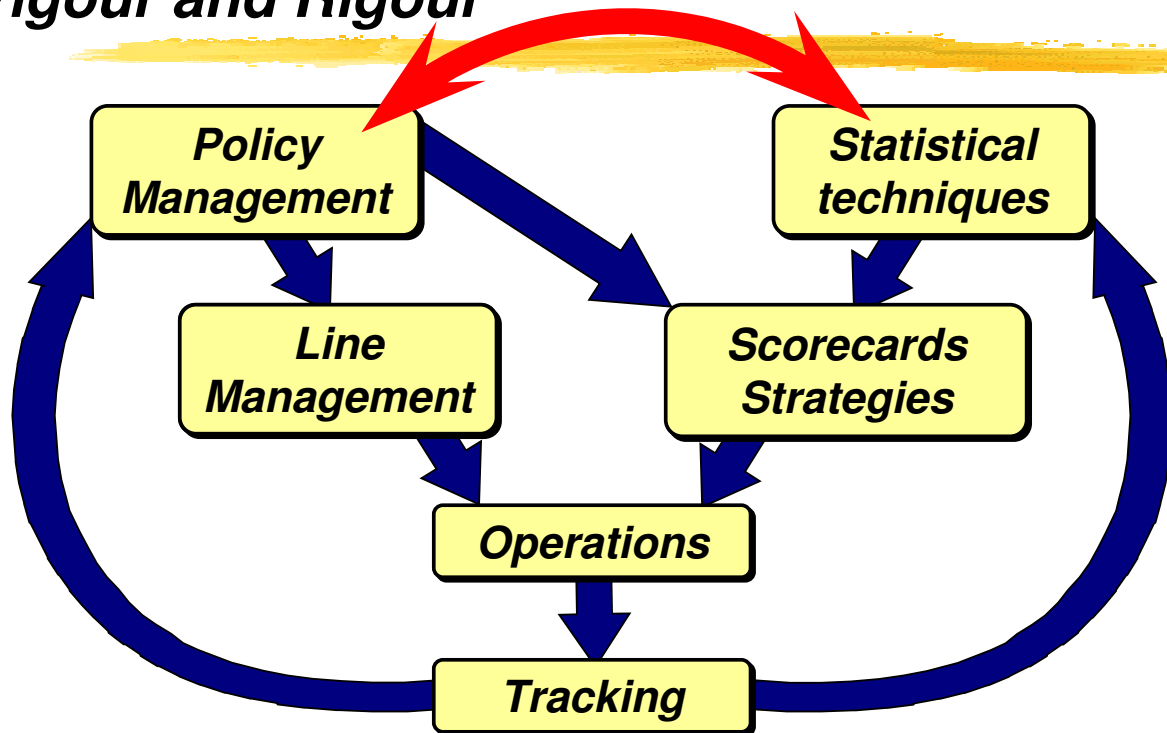
- ◆ Identify emerging variables
  - ◆ E.g. balance building
  - ◆ Potential additions to model
- ◆ Works with small samples
  - ◆ Chi<sup>2</sup> measures reliability
  - ◆ Useful results from 50-100 bads
- ◆ Works fast
  - ◆ 3-4 months after scoring
- ◆ Indicates quick (and dirty) corrective action
- ◆ Spots emergence from recession
  - ◆ Segments outperforming
  - ◆ Best time to be in business

## Practice

- ◆ Cheque Account
- ◆ Emerging market
- ◆ Mild excess more likely to deteriorate
- ◆ Strong vintage effect
  - ◆ short time on books
- ◆ Amount of excess balances matters more
- ◆ "Invulnerable" accounts unaffected
- ◆ Worst accounts don't deteriorate proportionately
  - ◆ "Permanent recession"

**Makes scoring models more transparent to ordinary people**

# The Management Link: *Vigour and Rigour*



## Key Management Consequences *Accountability*

- ◆ Fast recognition of changes in risk
  - ◆ ... and business consequences
  - ◆ ... and suggests what to do about it
- ◆ Accountability for performance
  - ◆ E.g. risk performance of marketing campaigns
  - ◆ What is changing and why?
- ◆ Better business integration
  - ◆ Blurs line between model development and management
  - ◆ Aligns risk feedback loop (nearly) to marketing cycle

**Makes scoring models more transparent to ordinary people**

# Open questions

- ◆ Continuous predictors
  - ◆ Analogue of Marginal IV
- ◆ Probabilities not homogeneous
  - ◆ Is  $\chi^2$  still robust?
- ◆ Alternative definitions of  $\Delta$ -scores
  - ◆ 1<sup>st</sup> iteration of Newton-Raphson
- ◆ Variance of  $\Delta$ -scores
  - ◆ Variance of expected WoE?
  - ◆ Use of re-sampling techniques
- ◆ Translate from log-odds language to PDese
- ◆ Sequential testing
  - ◆ Information from consistency of results over time?
- ◆ Extend to models other than Logistic Regression
  - ◆ Survival analysis
  - ◆ Balance and revenue models

**Some trivial – others not**