Monitoring & Maintaining Credit Bureau Scores

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Credit Scoring and Credit Control XI, Edinburgh 2009

Monitoring & Maintaining Credit Bureau Scores

- Credit Bureau data is highly predictive and an essential part of any application scorecard in the UK;
- Many credit providers use generic Credit Bureau scorecards as part of their application process;
- Credit Bureau scorecards are typically developed in quite a different way to traditional application scorecards;
- Issues involved in the on-going support of credit bureau scores have implications for all application scorecards.

Scorecard Monitoring
Rebuilding Scorecards

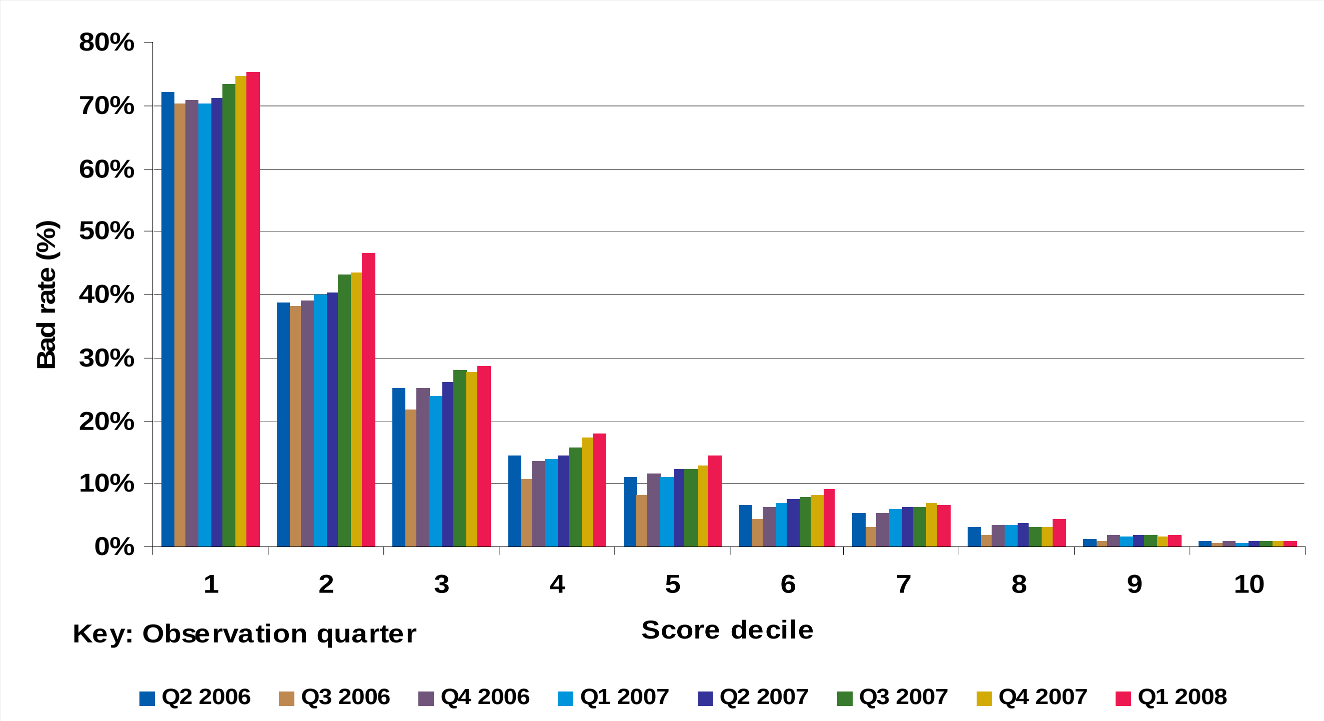
Scorecards deteriorate because of change in the applicant profile and the way in which characteristics predict future performance.

Need to establish a regular redevelopment cycle – interrupted if scorecard monitoring indicates significant loss of discrimination or because of economic factors.

Event impacting scorecard performance. → Collect 6-12 months of application data → Wait 6-12 months for outcome data → Scorecard development 3-6 months → Scorecard implementation 3 months → Scorecard goes live 18 months+ after the event

Data requirements for scorecard development make it difficult to react quickly to economic factors or data issues.

Scorecard Monitoring
Consumer Delphi Monitor



Banking and Finance Sector Bad Rates by Risk Segment: Q2 2006-Q1 2008

Monitoring & Maintaining Credit Bureau Scores
Agenda

- **Segmentation**
- **Geo-Demographic Data**
- **Over Indebtedness**
- **Optimising Scorecard Performance**

Monitoring & Maintaining Credit Bureau Scores
Agenda

Segmentation

Geo-Demographic Data

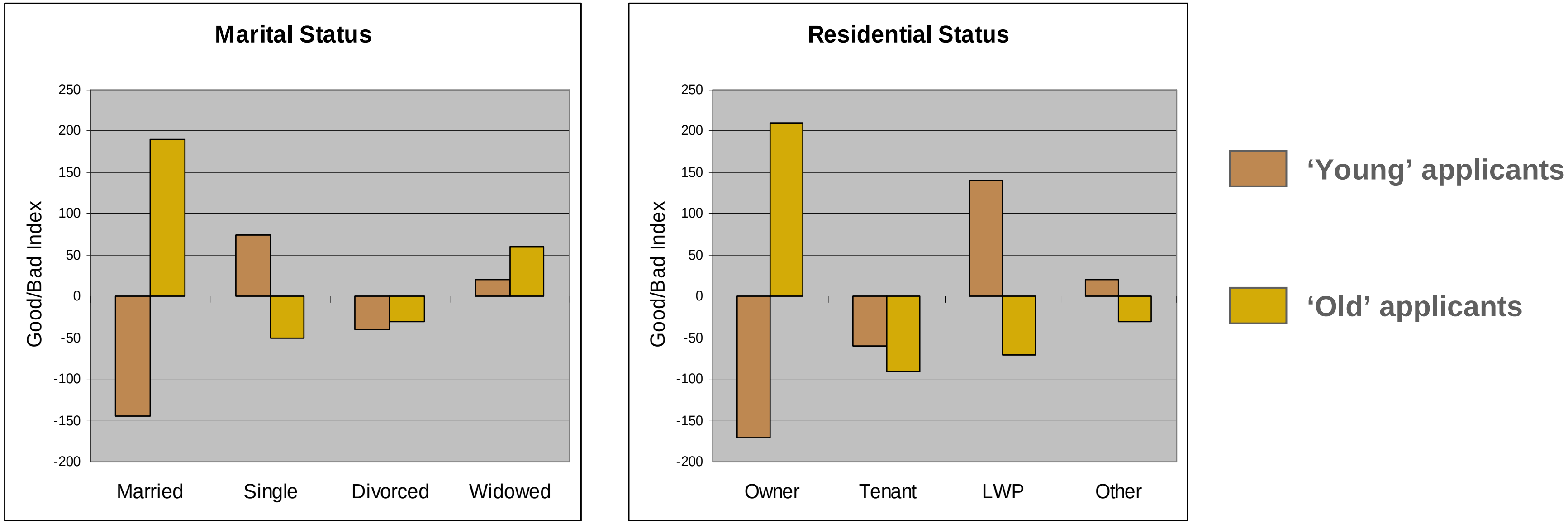
Over Indebtedness

Optimising Scorecard Performance

- Potential improvement in scorecard discrimination from segmentation on credit bureau data;
- Type of customer and product applied for should be considered.

Segmentation
Traditional Scorecard Segmentation

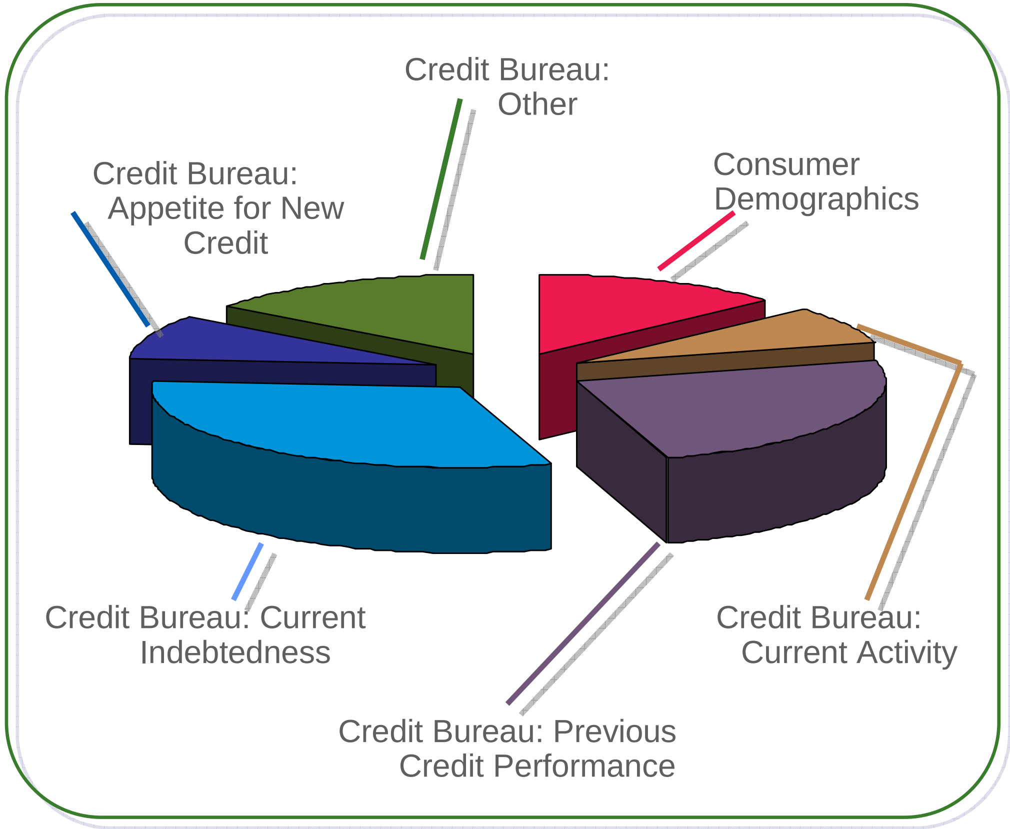
Application scorecards are typically segmented based on product, application channel or demographics such as age of applicant.



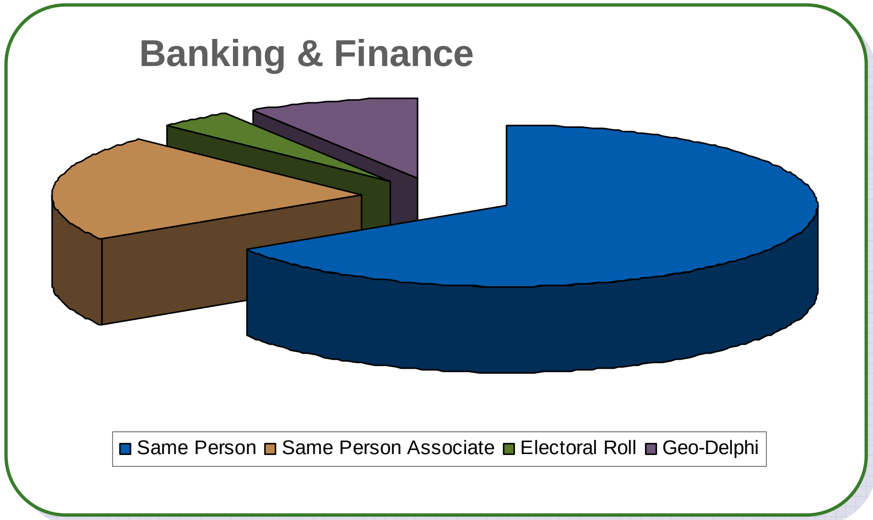
** Good/bad index measures the interval good/bad odds compared to the average*

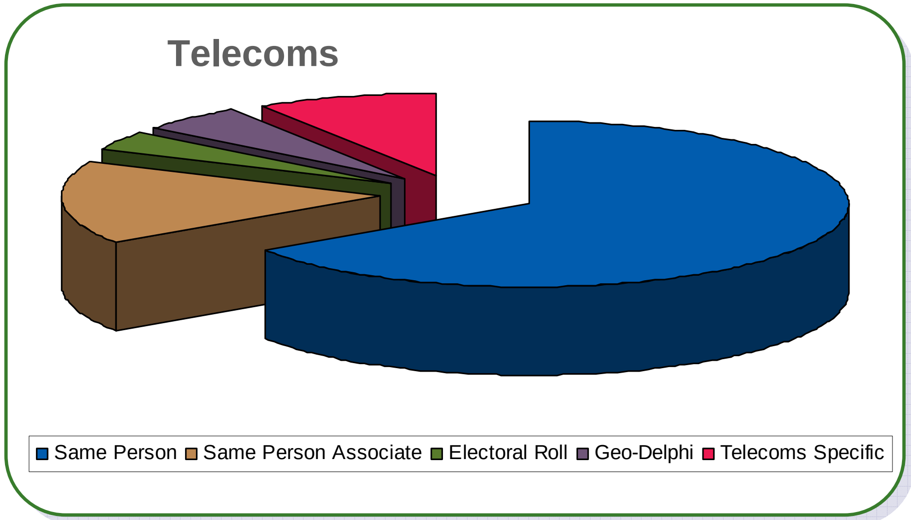
Segmentation
Importance of Credit Bureau Data

‘Full’ Credit bureau data is generally more important within an application scorecard than applicant demographics, typically contributing at least 85% of scorecard points.



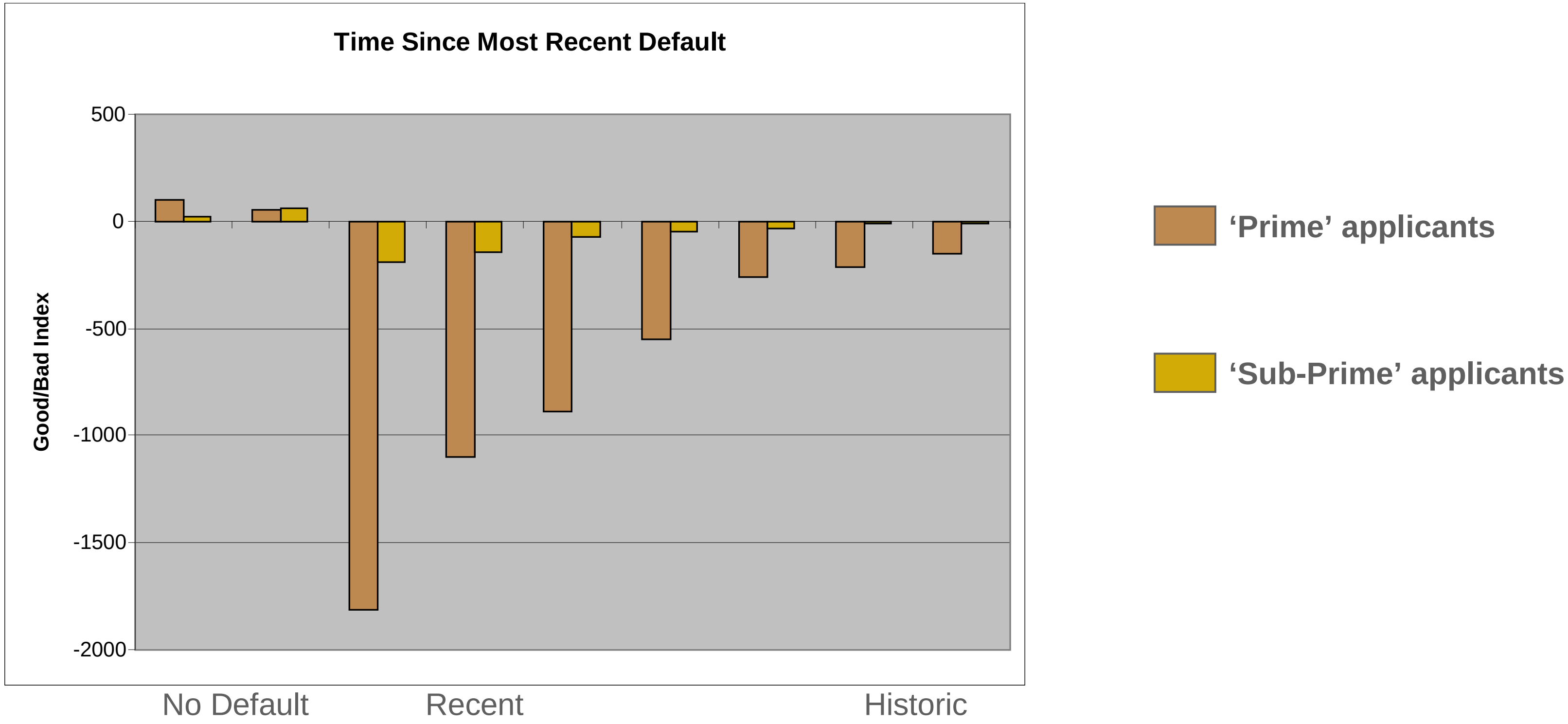
Segmentation
Telco Population Differences





Telecoms scorecard includes sector specific bureau references, which contribute around 9% of the power of the scorecard.

Segmentation
Sub-Prime Population Differences



** Good/bad index measures the interval good/bad odds compared to the average*

Segmentation
Strength of Credit Bureau Data

Derog	Serious payment problems (3+ down) or public information (Judgement, Bankruptcy etc).
New to Credit	No credit agreements more than 12 months old (including no accounts).
Credit Actives	At least one credit agreement more than 12 months old and outstanding balance (excluding mortgage) > £100.
Limited	All other applicants.

Segmentation
Strength of Credit Bureau Data

Sub-Population	Typical % Population	Bad Rate	Key Characteristics
Derog	20.9%	47.4	Time Since Most recent CAIS 8/9 Worst Status L6M for Accounts Open > 12M Balance on All Revolving CAIS
New to Credit	15.5%	24.3	Total Number of Searches L3M Worst Status L6M on All Active CAIS Highest Credit Limit Utilisation on Revolving Credit
Credit Active	45.6%	13.3	Average Age of CAIS in Months Worst Status L6M on All Active CAIS Balance on All Active Non-Revolving CAIS
Limited	17.0%	5.7	Total Number of Searches (Non-Mail Order) Non-Mail Order CAIS Delinquent (SPA) Total Number of Credit Card Searches L3M

** The ‘key’ characteristics are based on the largest points contribution to each respective scorecard. Geo-Delphi and CII are excluded – these products are explained later in the presentation.*

Segmentation
Strength of Credit Bureau Data

Score Band	Derog		New to Credit		Credit Active		Limited	
	% Popln	G:B Odds	% Popln	G:B Odds	% Popln	G:B Odds	% Popln	G:B Odds
1	50.3%	0.1:1	9.2%	0.3:1	4.8%	0.2:1	1.1%	0.5:1
2	15.8%	0.7:1	4.9%	1.0:1	2.9%	0.8:1	0.5%	0.7:1
3	12.9%	1.5:1	7.0%	1.5:1	5.6%	1.7:1	1.1%	1.8:1
4	8.8%	3.4:1	44.8%	3.2:1	7.9%	3.4:1	2.84%	2.9:1
5	12.2%	12.0:1	28.1%	13.3:1	7.5%	8.8:1	6.7%	6.6:1
6	0.0%	-	0.0%	116.0:1	14.7%	20.0:1	14.9%	21.3:1
7	0.0%	-	0.0%	-	29.0%	50.1:1	36.35%	118.1:1
8	0.0%	-	0.0%	-	27.7%	213.9:1	36.47%	305.8:1

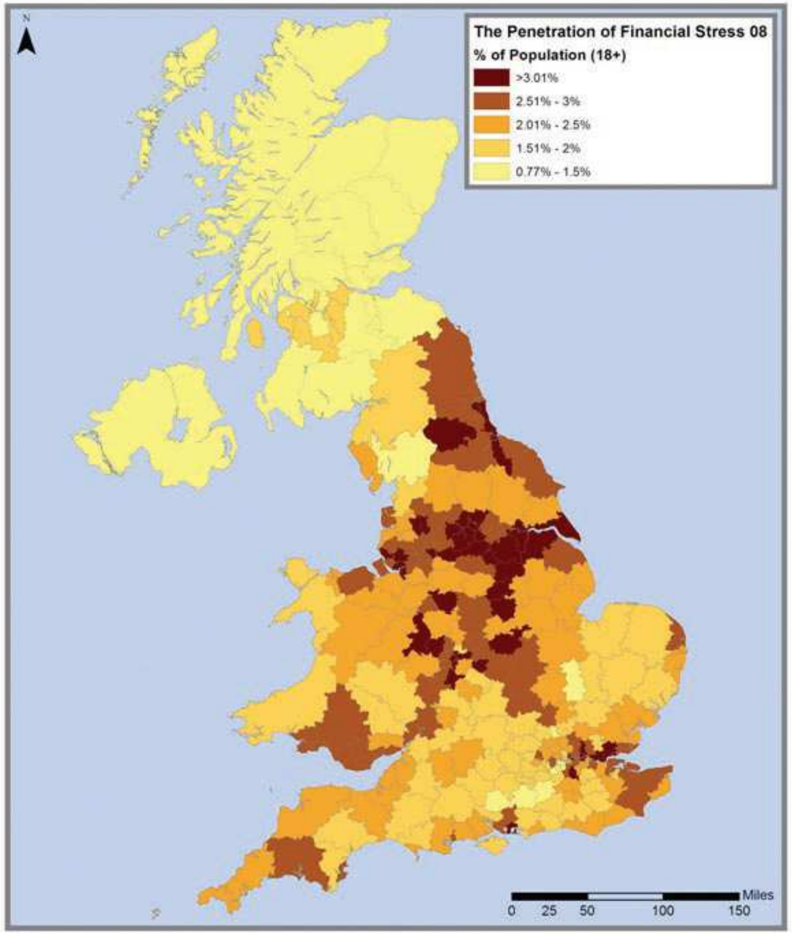
Gini	76.6	68.2	82.6	81.2

Monitoring & Maintaining Credit Bureau Scores
Agenda

- **Segmentation**
- **Geo-Demographic Data**
- **Over Indebtedness**
- **Optimising Scorecard Performance**

- Geo-demographic data is highly predictive of future risk;
- To harness the full power of the data a separate model is required;
- Embedding a geo-demographic model within a credit bureau scorecard can increase overall discrimination by over 13%.

Geo-Demographic Data
Importance of Geo-Demographic Data



Financial stress has been determined by new instances of IVA, bankruptcy (sequestration in Scotland) and CCJ.

Data available at post code and postal sector level, for example:

- % houses with defaults;
- % houses with worst arrears status L6M 4+;
- % houses 5+ searches L3M.

Geo-Demographic Data
Modelling Geo-Demographic Data

Individual geo-demographic characteristics will not enter a typical scorecard.

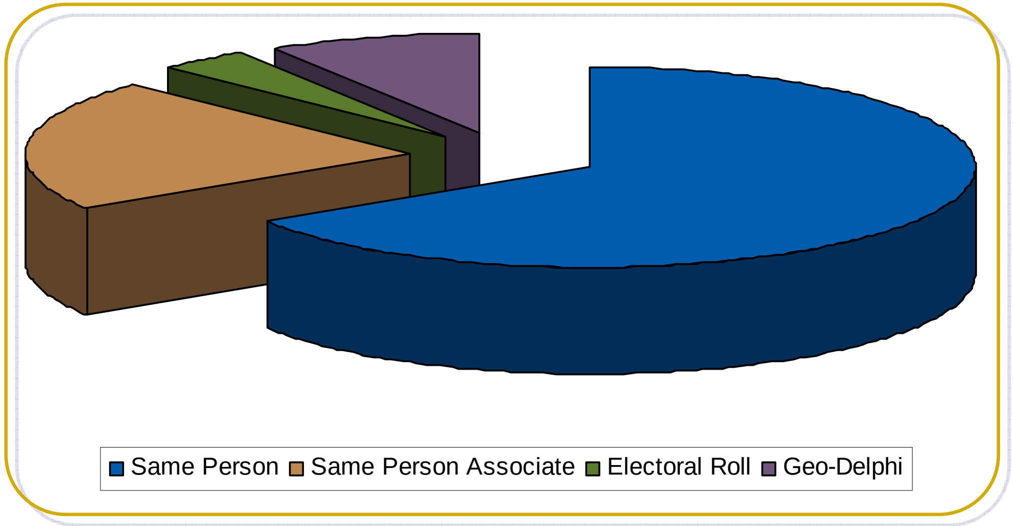
To leverage the full power of the geo-demographic data available a separate model is developed.

The resulting model (e.g. Experian's Geo-Delphi) can then be embedded within an application scorecard or Credit Bureau Score.

Geo-Delphi	Good/Bad Odds	% UK Postcodes
1	> 30.0:1	10.9%
2	20.1-30.0:1	10.2%
3	13.1-20.0:1	7.2%
4	9.1-13.0:1	12.8%
5	5.1-9.0:1	18.8%
6	3.6-5.0:1	13.2%
7	2.6-3.5:1	9.5%
8	1.6-2.5:1	10.5%
9	<= 1.5:1	6.9%

Geo-Demographic Data
Contribution of Geo-Demographic Data

Within a typical Credit Bureau Scorecard Geo-Demographic data will contribute around 10% of the points within the scorecard.



Improvement to Credit Bureau Scorecards from the use of Geo-Demographic data (assessed based on Gini co-efficient) can be up to 13.5% - though this will vary depending upon the strength of credit bureau data.

Geo-Demographic Data
Monitoring Geo-Delphi

Stability of Geo-Demographic data is a consideration.

Post code and Postal sector data needs to be refreshed periodically.

Quarter	GINI
Q2 2006	42.12
Q3 2006	36.80
Q4 2006	37.28
Q1 2007	37.61
Q2 2007	37.21
Q3 2007	34.65
Q4 2007	38.05
Q1 2008	38.66

Retail Sector Geo-Delphi Index

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- **Segmentation**
- **Geo-Demographic Data**
- **Over Indebtedness**
- **Optimising Scorecard Performance**

- Over indebtedness is not always identified within a traditional scorecard;
- Debt profile credit bureau characteristics can contribute significantly;
- Indebtedness at 'outcome' can be incorporated into the good/bad flag.

Over Indebtedness
Why Debt Profile is Important

Responsible lending necessitates consideration of consumer indebtedness.

The statistics below were compiled from a sample of credit applications (Q3/Q4 2007) that had not had any payment difficulties within the previous 6 months.

Customer Type	% Applications	Default within 12 months
Unsecured borrowing > £25,000	4.9%	1 in 4
Unsecured borrowing > £50,000	1.0%	1 in 2
Revolving CL > £15,000 and CLU > 80%	0.6%	1 in 2
5+ Accounts with Balance > £1000	2.6%	1 in 3

Over Indebtedness
Indebtedness within the Good/Bad Flag

Consumers with a high level of indebtedness represent an unacceptable risk to most credit providers.

By classing highly indebted cases (at outcome) as bad it ensures that the scorecard discriminates against these applicants.

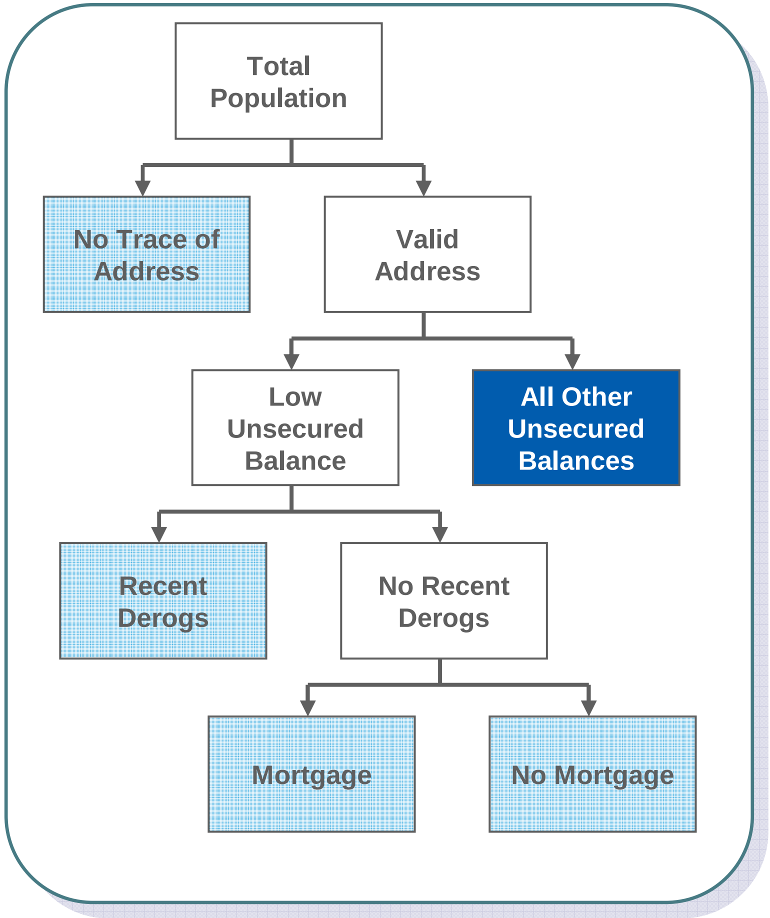
Traditional Good/Bad Flag

Reject Rate	Bads Identified	Over Indebted	Total Bads
10%	40.8%	16.2%	**36.2%**
20%	62.2%	33.5%	**56.8%**
30%	74.5%	48.3%	**69.6%**
40%	84.0%	63.6%	**80.1%**
50%	89.8%	75.8%	**87.2%**

Good/Bad Flag with Indebtedness

Reject Rate	Bads Identified	Over Indebted	Total Bads
10%	42.9%	21.8%	**38.9%**
20%	65.8%	49.5%	**62.8%**
30%	79.6%	68.7%	**77.6%**
40%	87.8%	81.6%	**86.6%**
50%	92.2%	88.4%	**91.4%**

Over Indebtedness
Modelling Debt Profile



Debt profile characteristics are predictive but will make a less significant contribution than other credit bureau characteristics.

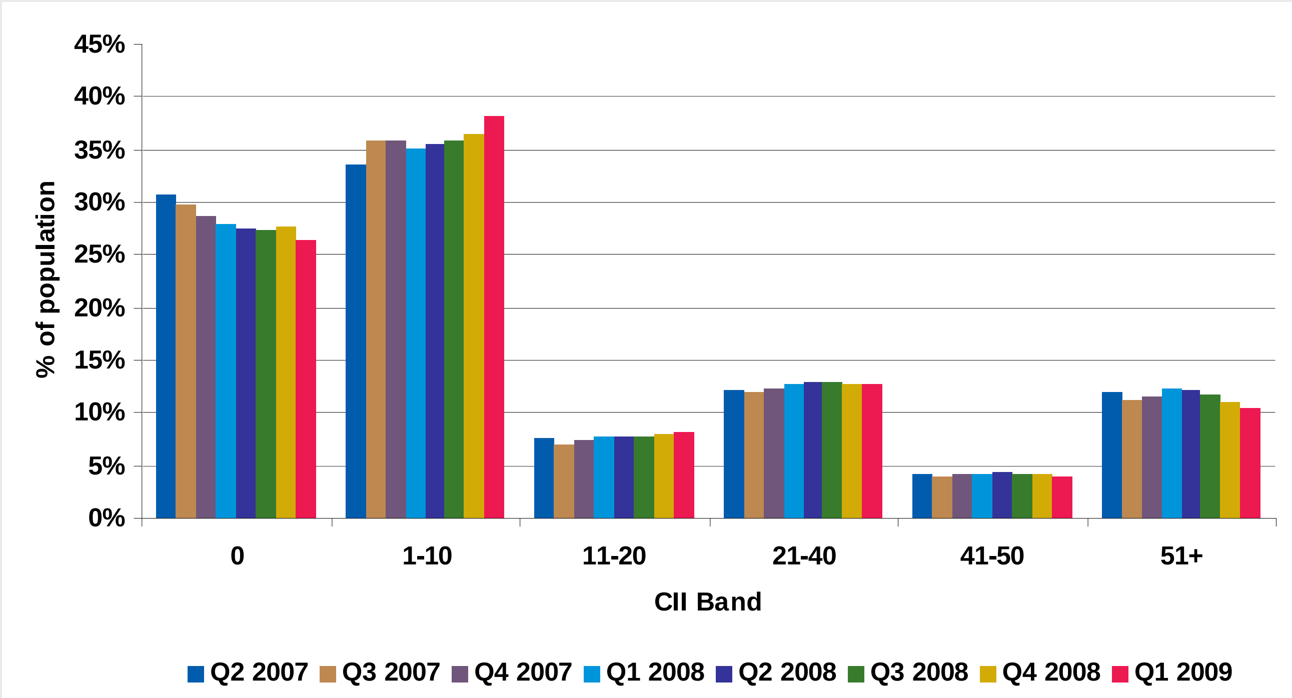
Developing a risk scorecard based on applicants who have 'significant' borrowing but no recent payment problems enables more emphasis to be placed on debt profile characteristics.

This is the basis for Experian's Consumer Indebtedness Index (CII).

Over Indebtedness
Modelling Debt Profile

CII Gen 3	# Consumers	% Consumers	Good/Bad Odds	Bad Rate
Recent Derog Data	15931	6.03	0.89	41.28
Trivial Balance	80399	30.44	6.03	13.30
No Trace	2811	1.06	6.92	0.86
1-10	87663	33.2	27.78	3.35
11-20	16279	6.16	4.66	15.22
21-30	15533	5.88	2.25	25.16
31-40	7755	2.94	1.28	34.17
41-50	15048	5.70	0.66	46.41
51-60	7497	2.84	0.29	59.80
61-70	7475	2.83	0.14	69.65
71-85	7761	2.94	0.04	83.72

Over Indebtedness
Monitoring CII Gen. 2



Banking and Finance CII Distribution by Quarter: Q2 2007-Q1 2009

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Segmentation

Geo-Demographic Data

Over Indebtedness

Optimising Scorecard Performance

- Use Segmentation to make best use of all your available data – consumer demographics and bureau data.
- Include geodemographics – particularly where your consumer data is thin.
- Remove over-indebted cases from the goods and include an indebtedness metric within all your credit scoring models.

Optimising Scorecard Performance
Delphi for New Business Generation 9 Results

Segmentation gives significant improvement in scorecard discrimination. For example the improvement in Gini is 24.4% for Recent Derogs and 9.8% for Limited data.

Sub-Population	Improvement from Indebtedness Data	Improvement from Geo-Demographic Data	Delphi Gen 9 Gini
Derog	4.9%	2.8%	76.6
New to Credit	1.8%	13.5%	68.2
Credit Active	9.3%	3.7%	82.6
Limited	3.0%	10.7%	81.2

Note that results quoted vary across different sub-populations (Banking and Finance, Retail, Telco and Sub-Prime).

Experian

A world of insight

Experian