Under-Exposed

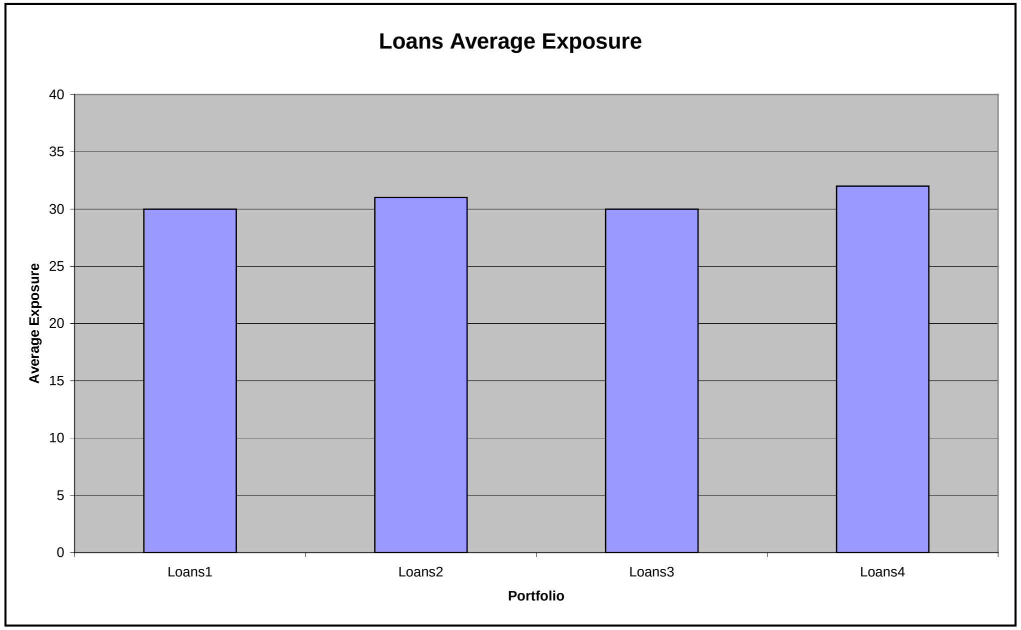
Gaynor Bennett

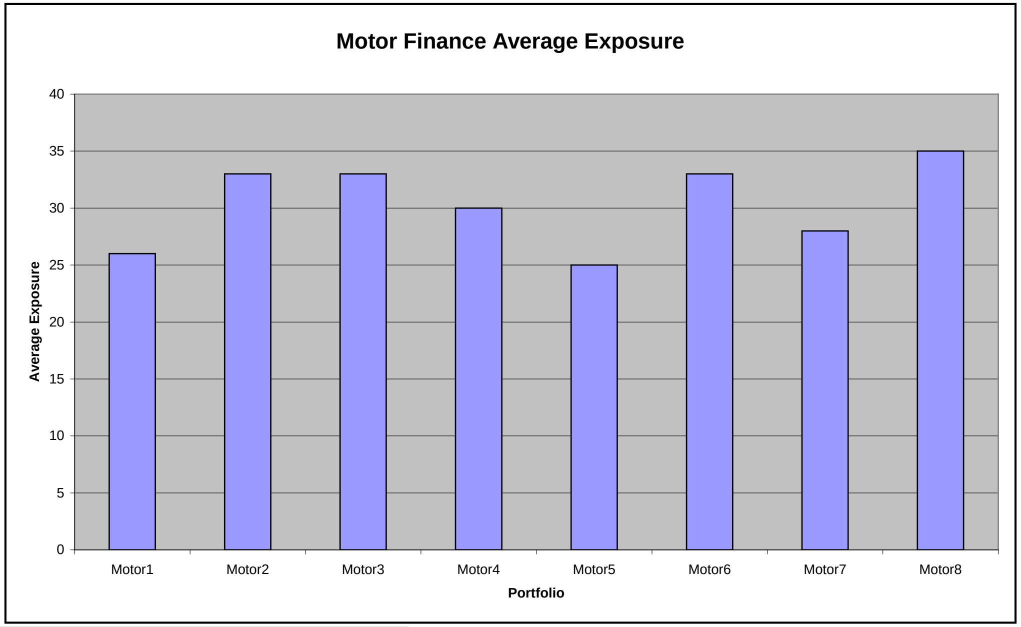
The Investigation

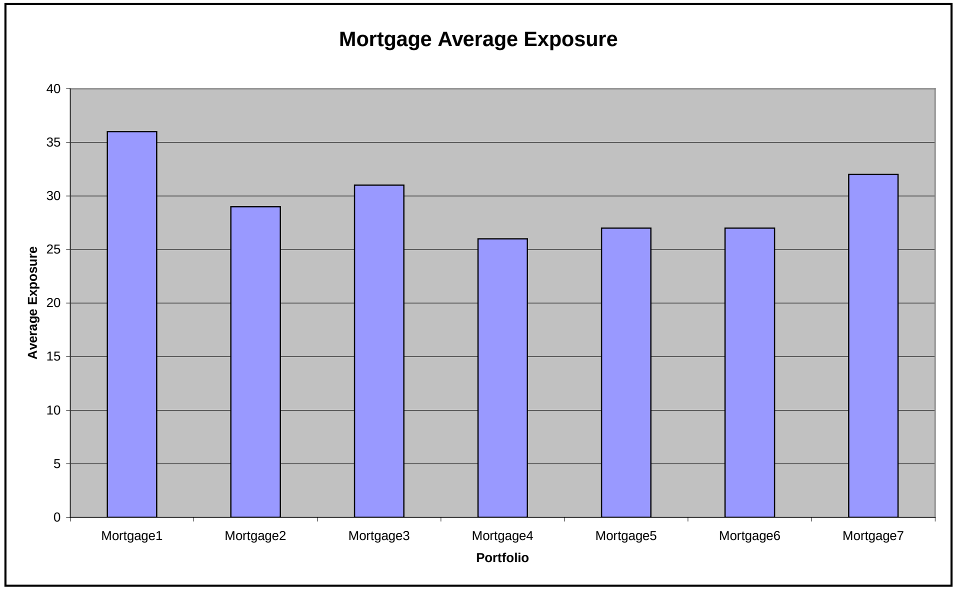
What Will Be Revealed?

- Industry case studies
  - Personal Loans
  - Motor Finance
  - Retail
  - Mortgages
  - Credit Cards
- Analysis samples
- Extent & effect of good/bad misclassification
- Model & comparison approach
- Results
- Conclusion

Industries – Typical Exposure Periods







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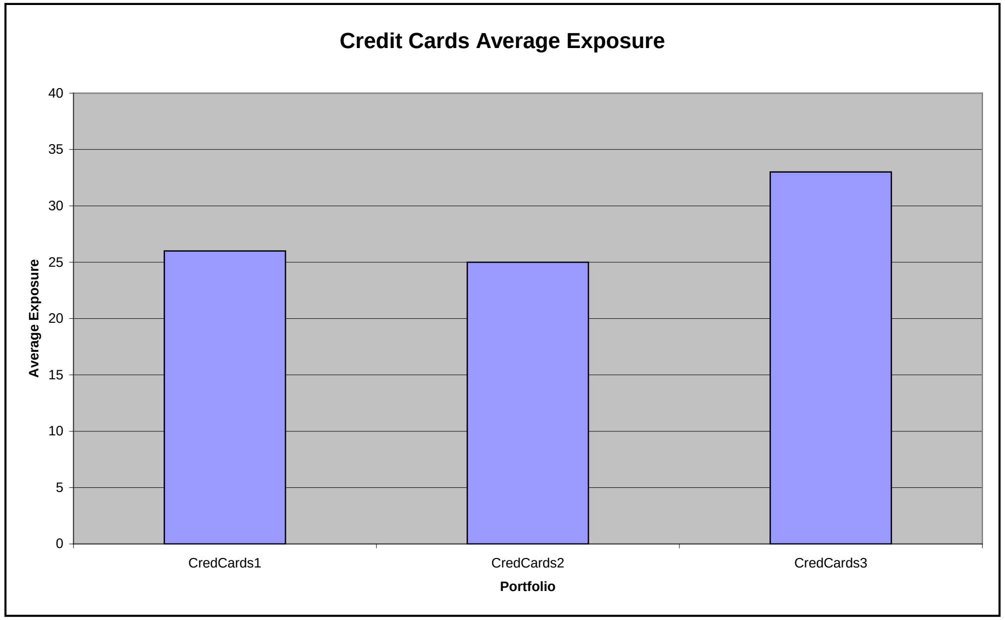
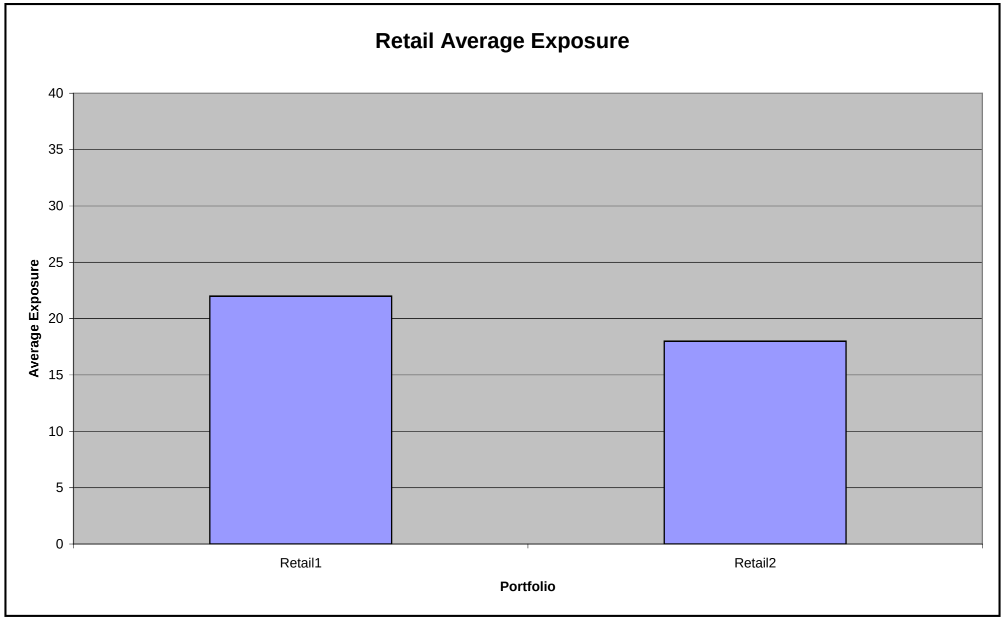
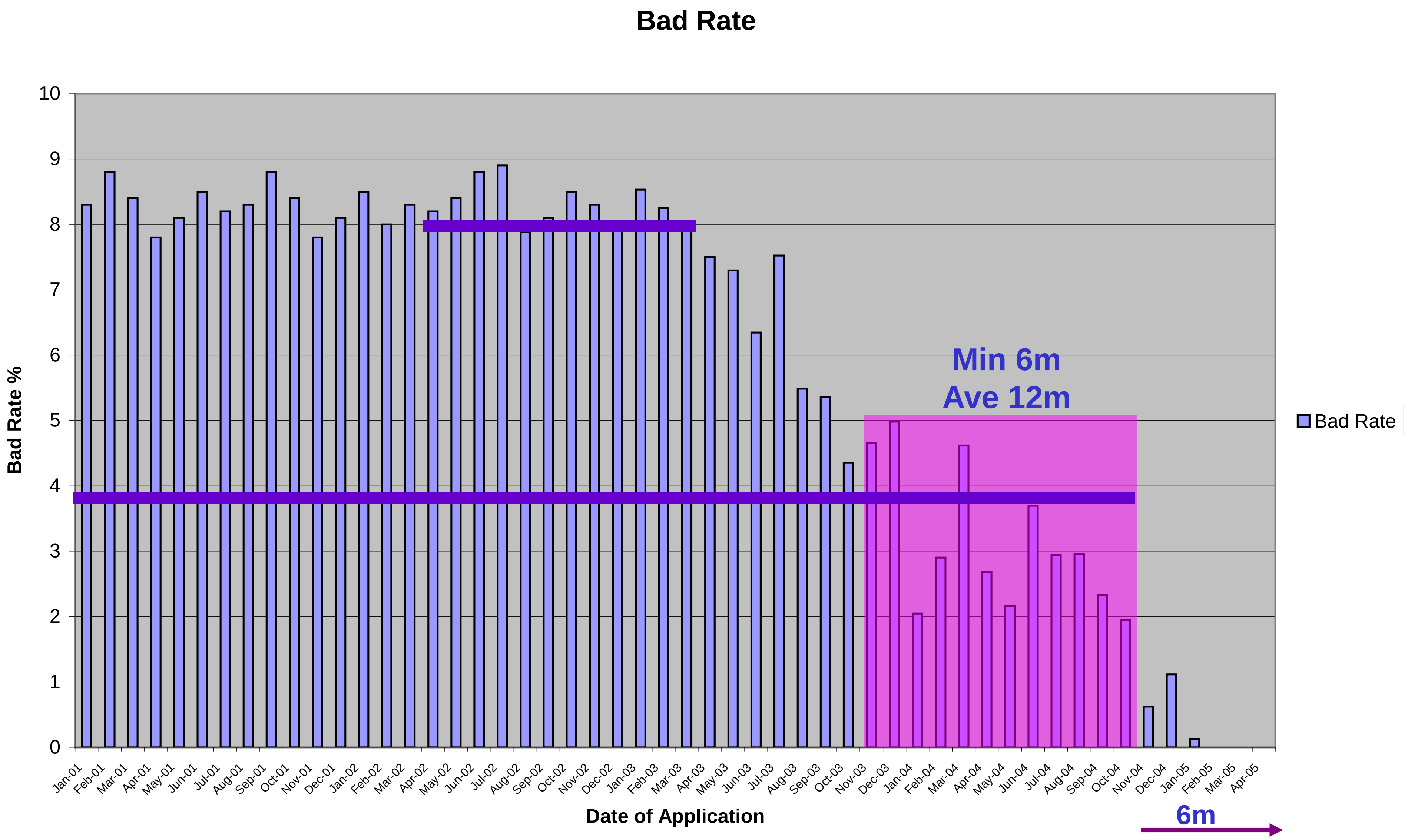




Under-Exposed Samples



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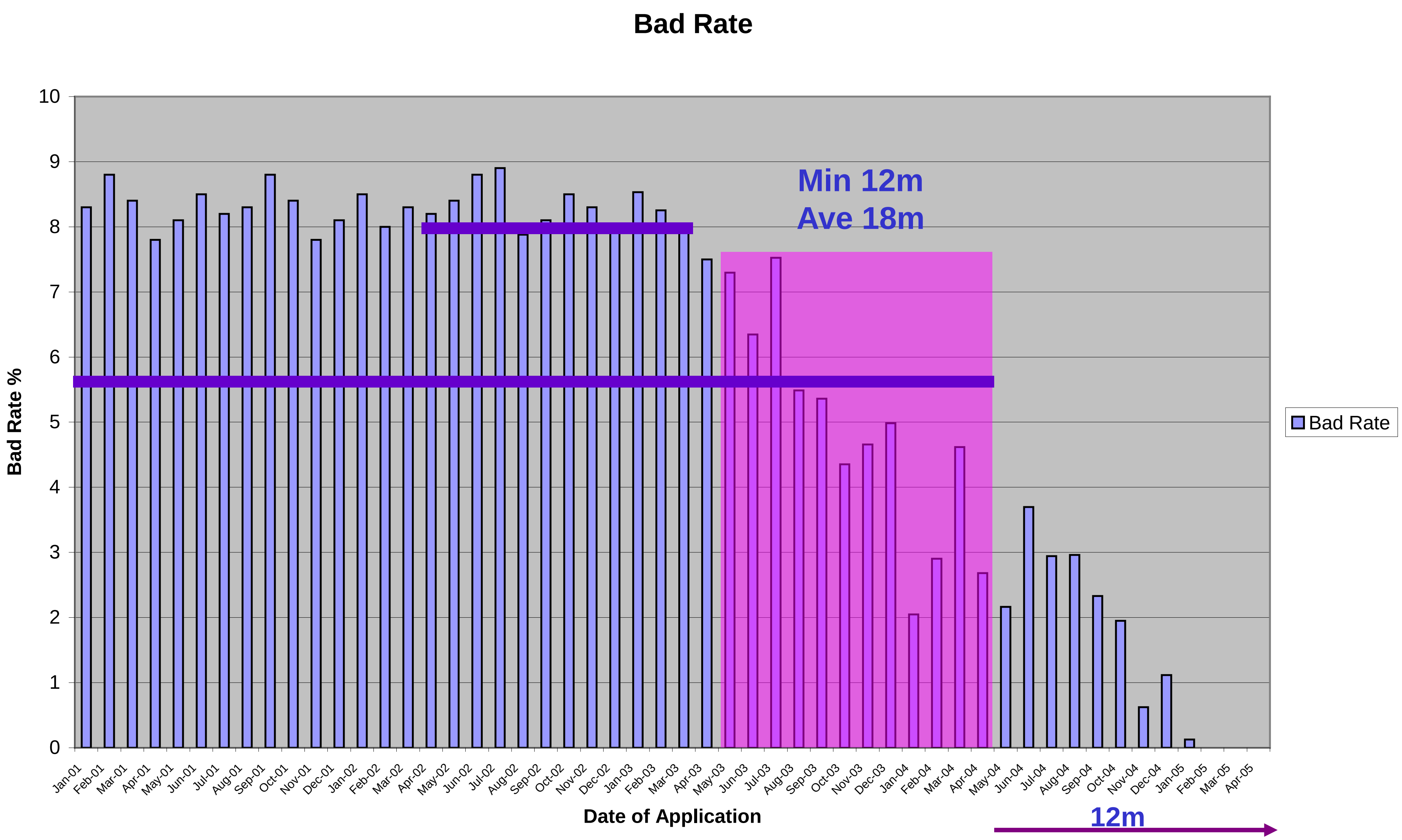

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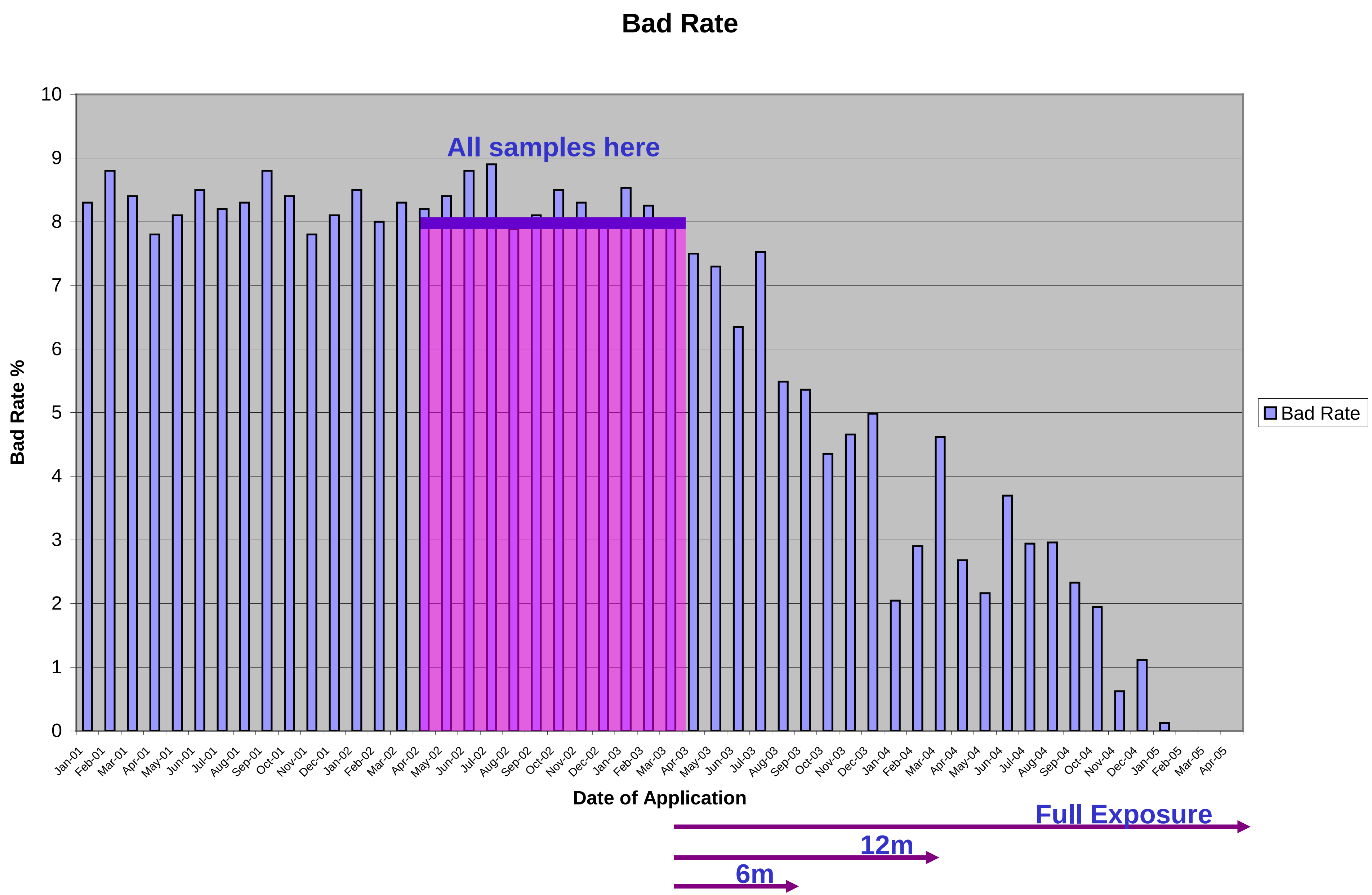


Good/Bad Classification

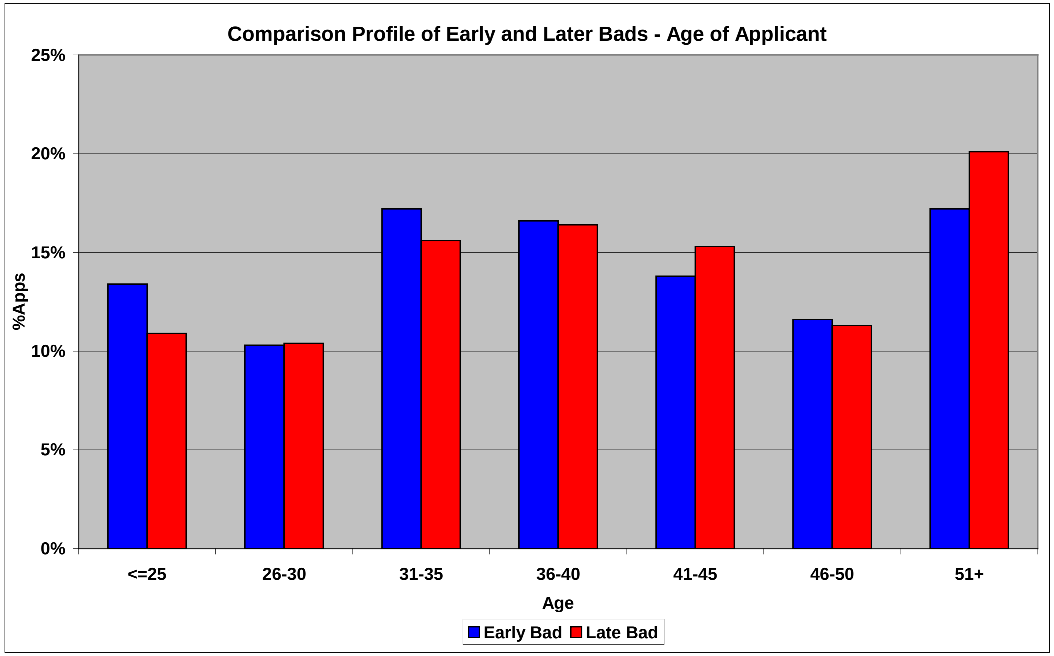
- Conventional
  - Bad = worst status 3+ in arrears
  - Indeterminate = worst status 2 in arrears
  - Good = worst status 1 in arrears
- Adjusted
  - Bad = worst status 2+ in arrears
  - Indeterminate = worst status 1 in arrears
  - Good = worst status 0 in arrears
- Credit Cards Adjusted
  - Bad = worst status 2+ in arrears
  - Indeterminate = empty
  - Good = worst status 1 in arrears

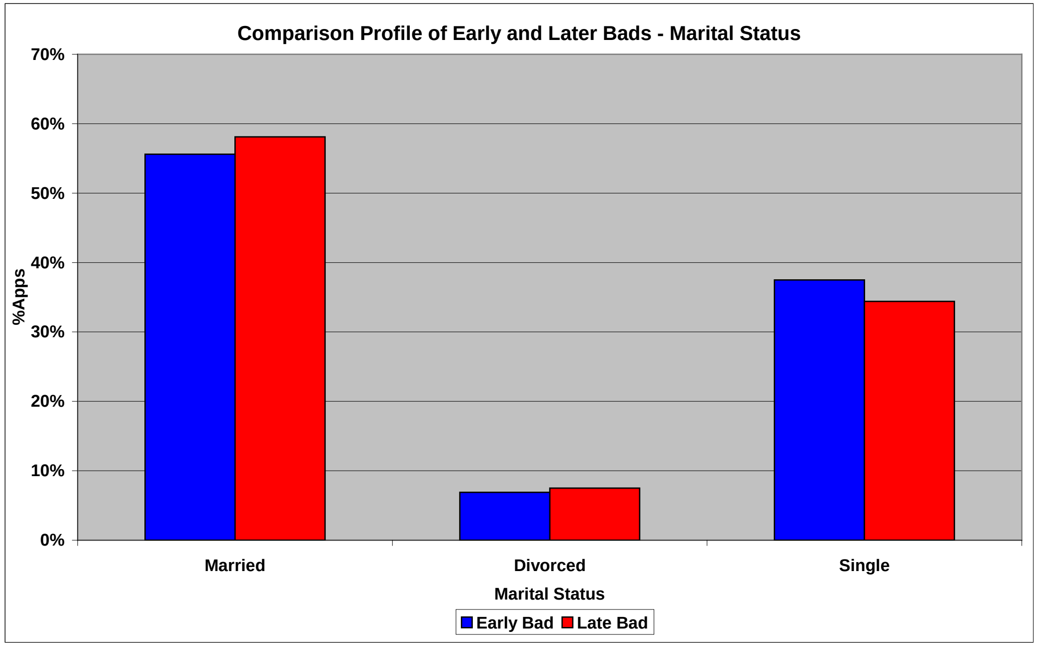
Good/Bad Misclassification

- For Personal Loans – Full Exposure average 33m
- After 6m min exposure (average 12m)
  - of the ultimate bads

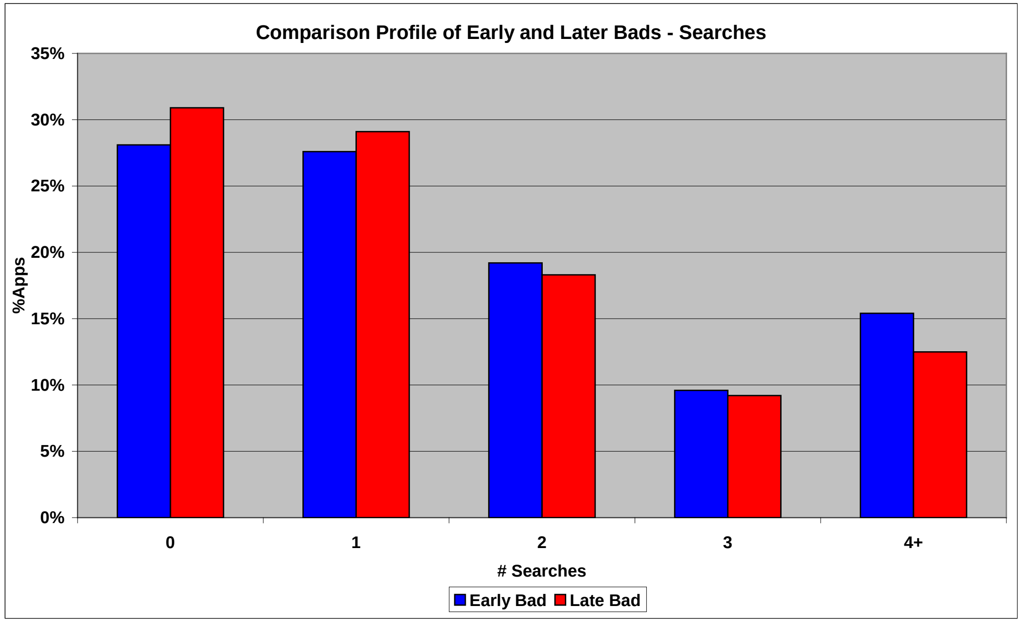
- But did the early and ultimate bads look different?
- And would this affect predictive strength of criteria?

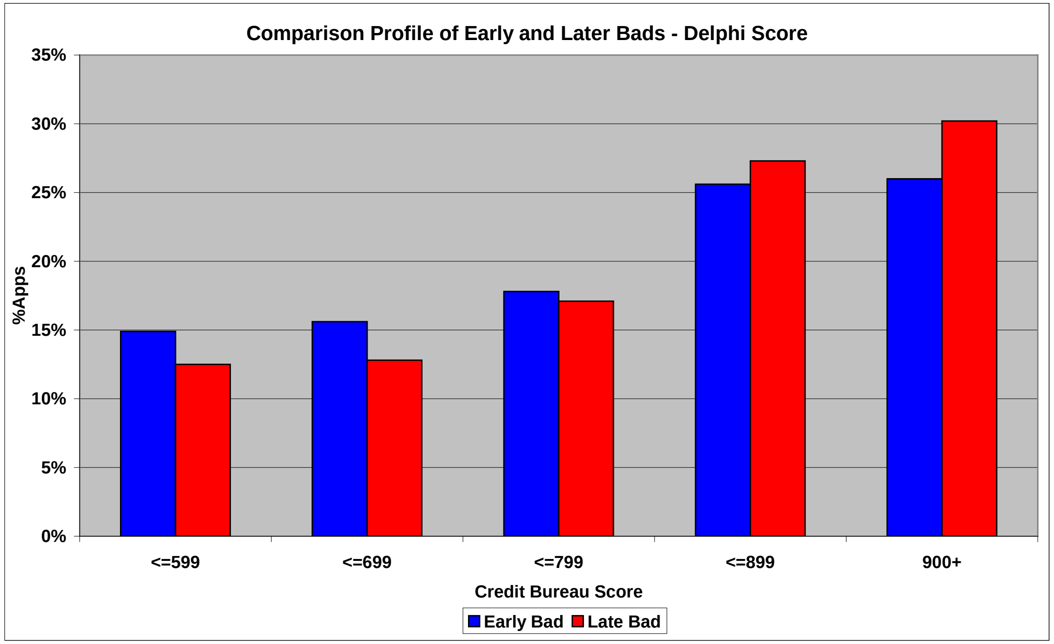
Comparison of Bad Profiles





Comparison of Bad Profiles



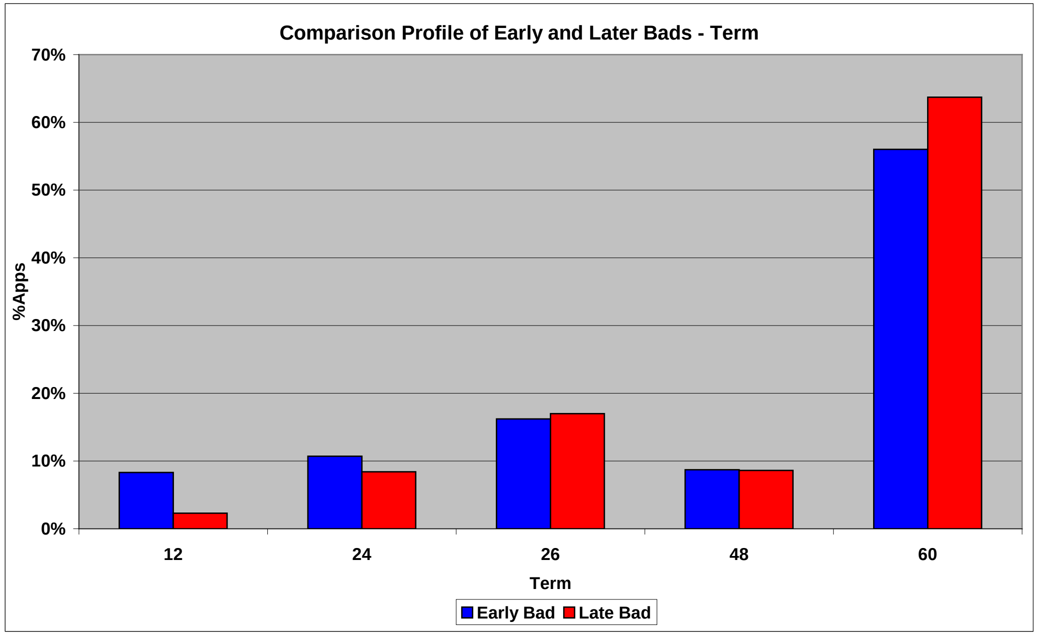


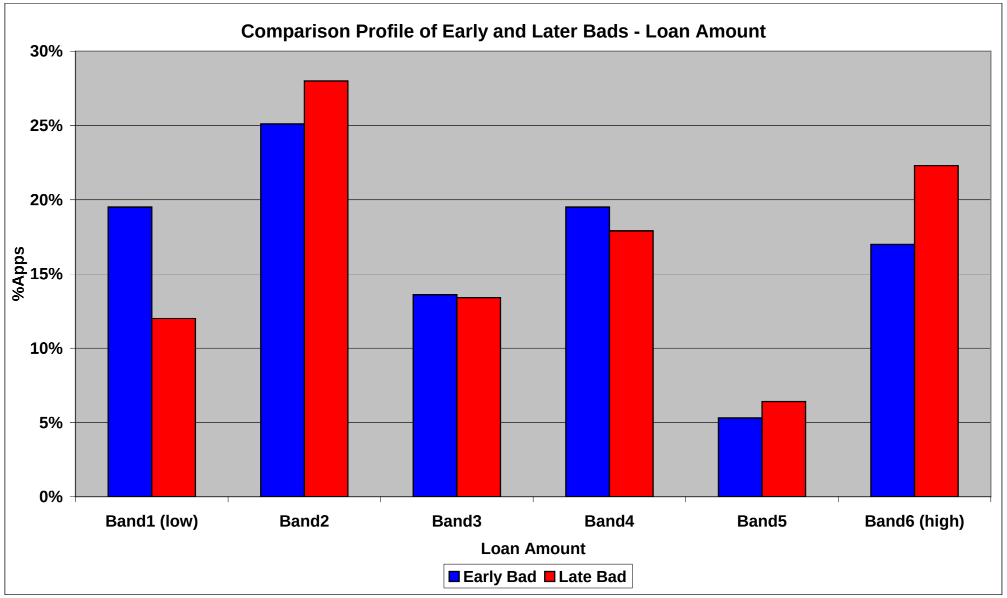
- Early bads worse

  but….

Comparison of Bad Profiles

- Not the case for time-related loan details



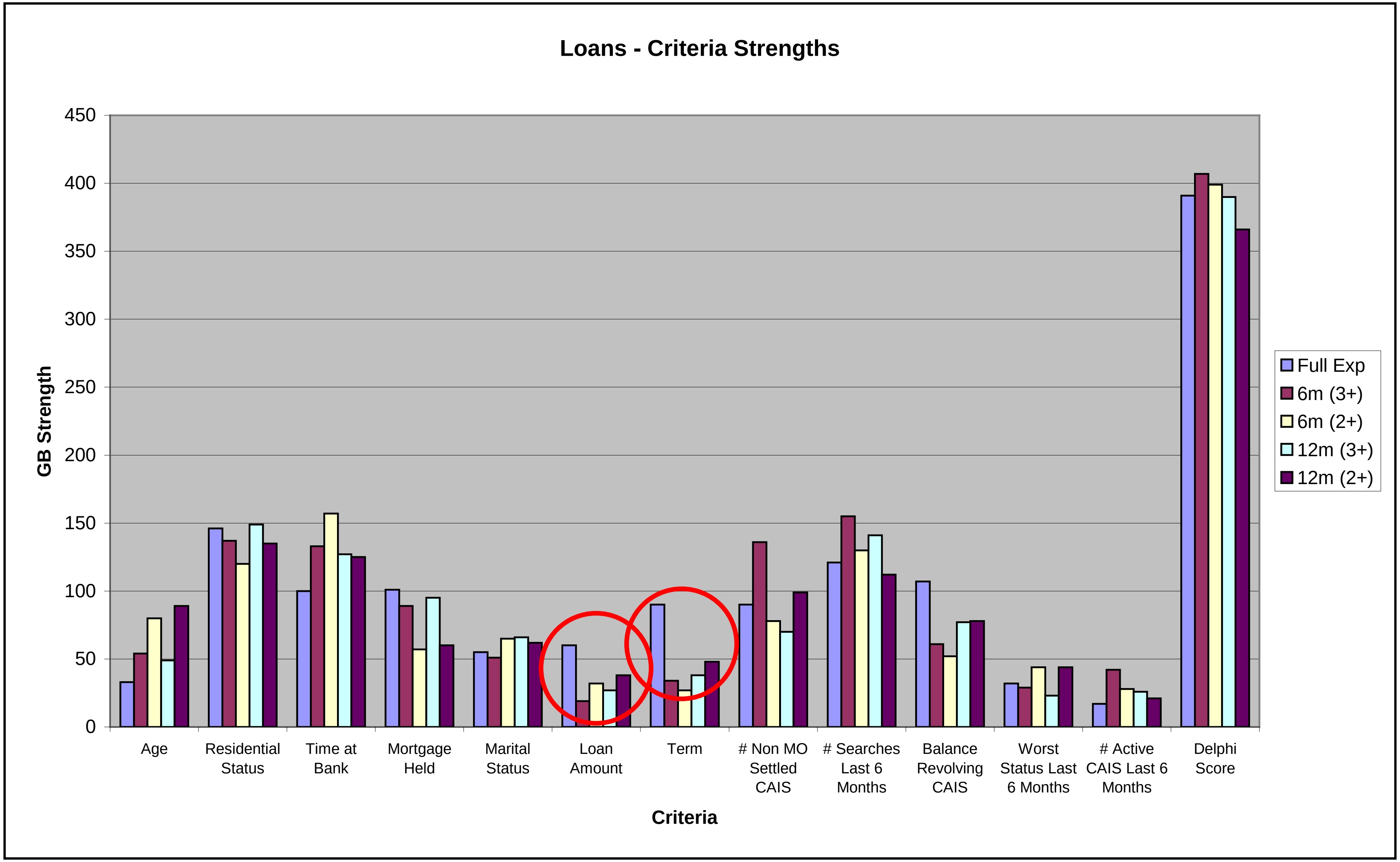


Impact on Predictive Strength

- Criterion strength = Information Value
  - Based upon proportions of goods and bads across attributes
  - GB strength

$$\text{Criterion strength} = \sum \left(\frac{(\%\,\text{Goods} - \%\text{Bads}) \times \left[\ln \left(\frac{\%\,\text{Goods}}{\%\,\text{Bads}} \right) \times 100 \right]}{10} \right)$$

Impact on Predictive Strength

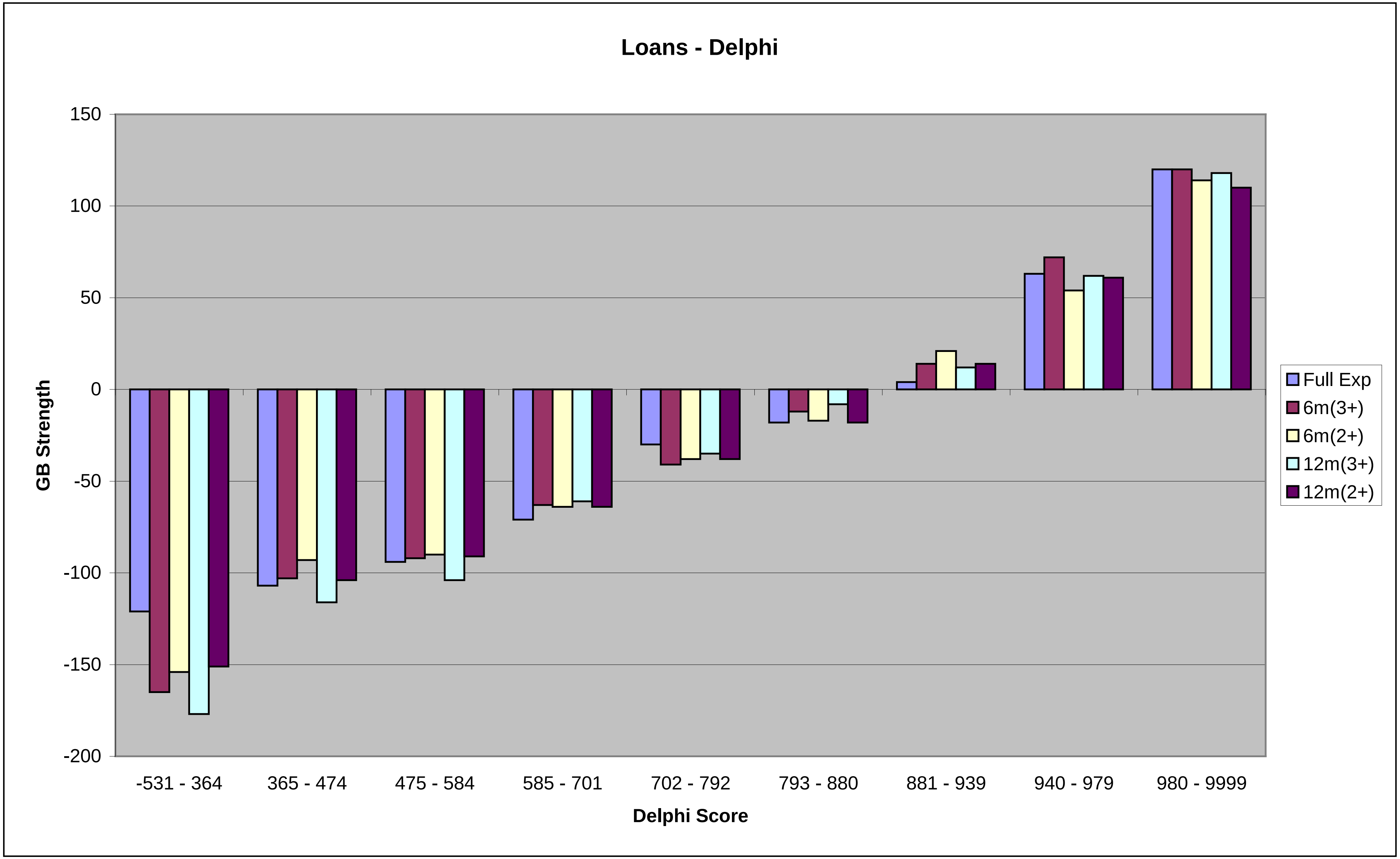


Impact on Predictive Strength

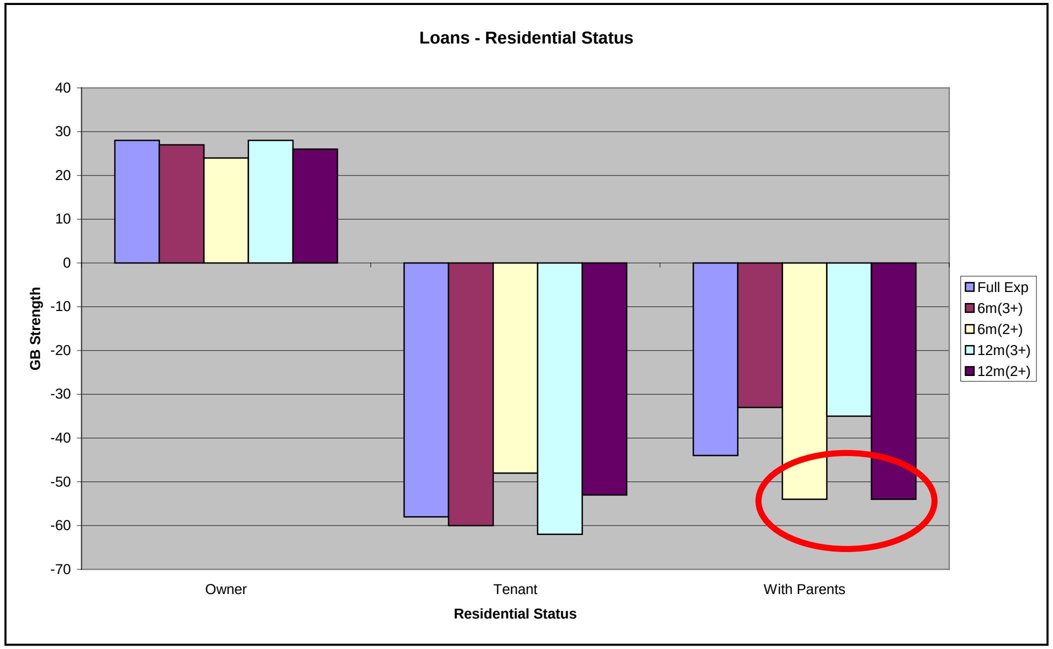
- Predictive Nature =
  Pattern of Weights of Evidence for attributes
  - GB attribute strength

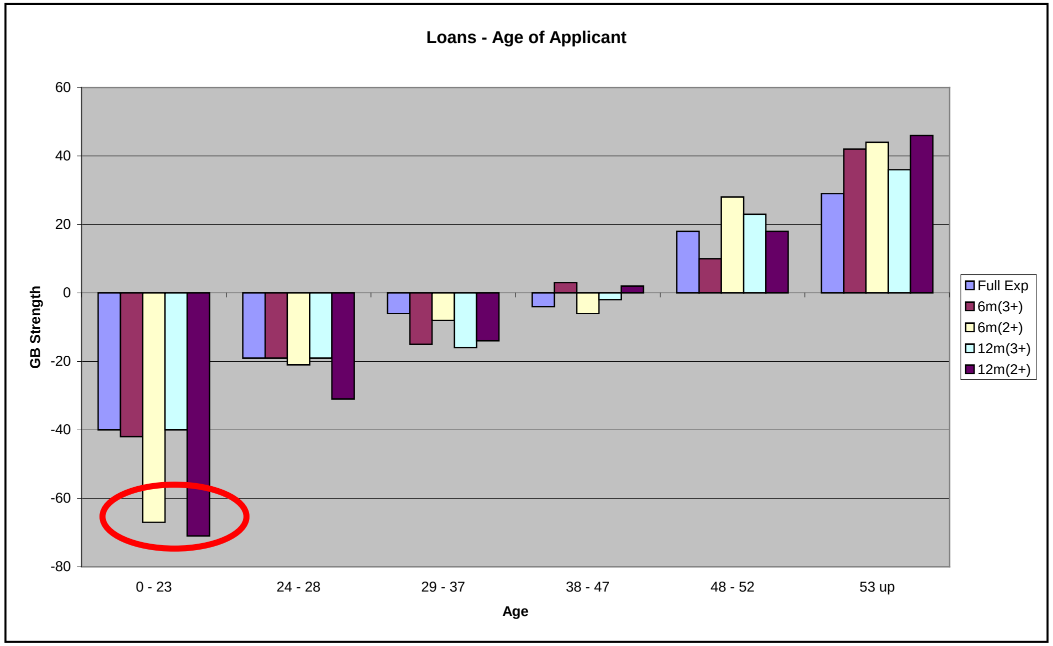
$$\text{Criterion strength} = \sum \left(\frac{(\%\,\text{Goods} - \%\text{Bads}) \times \left[\ln \left(\frac{\%\,\text{Goods}}{\%\,\text{Bads}} \right) \times 100 \right]}{10} \right)$$

Predictive Nature - Delphi

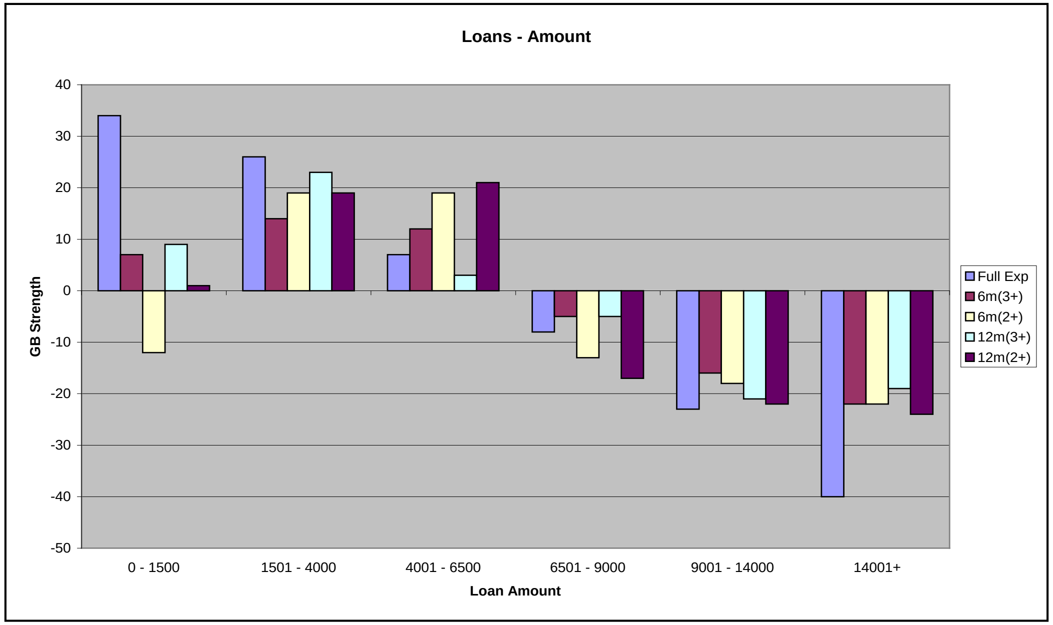


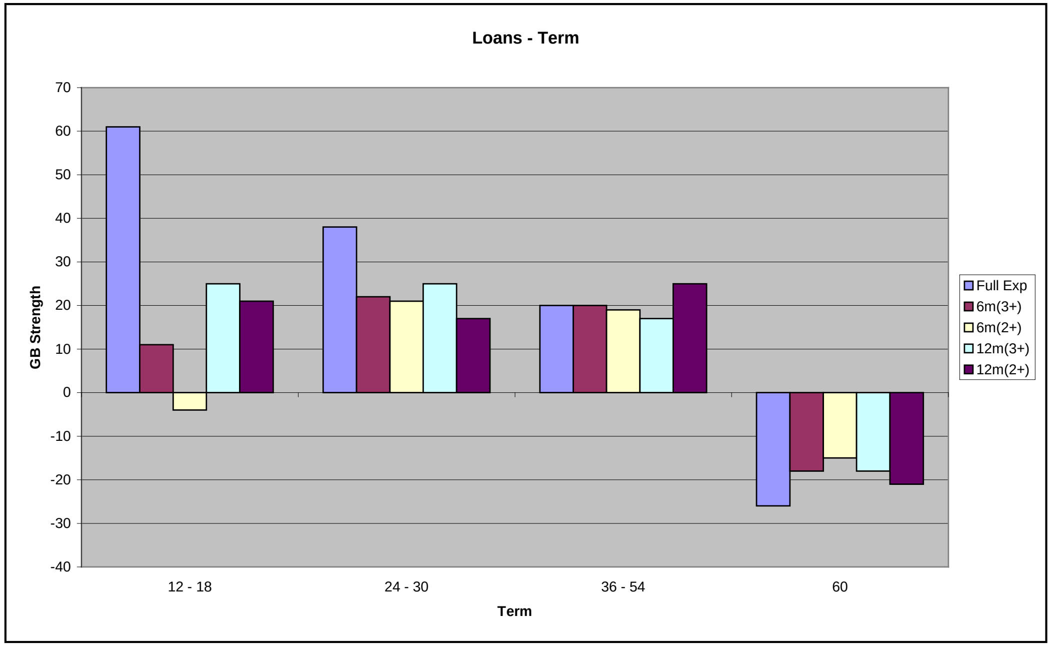
Predictive Nature – Residential Status & Age





Predictive Nature – Loan Amount & Term





Comparison of Predictive Strength

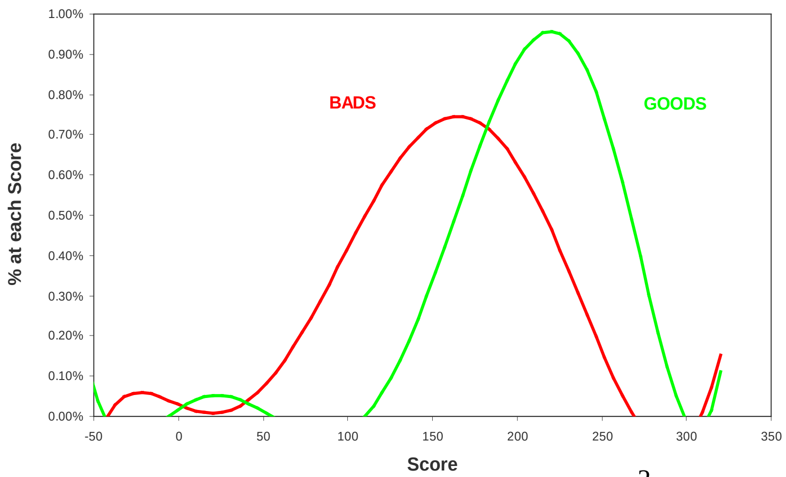
- Predictive power retained on 3+ definition
- Slightly weaker on 2+ definition
  - some difference in patterns
- Looked promising for scorecard modelling
  - time-related loan details best avoided

Model Comparison Approach

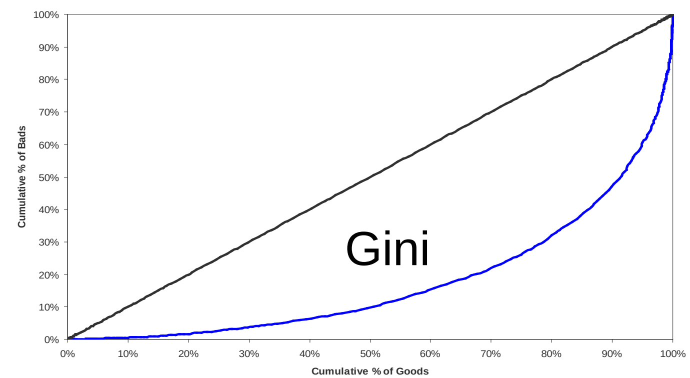
- Develop scorecards for all samples
  - FullExp
  - 6m(3+)
  - 6m(2+)
  - 12m(3+)
  - 12m(2+)
- Known good/bads only
  - reject inference similar across samples – but could bias comparison
- Same criteria and groupings in scorecards
  - negligible impact
- Minimal manual point adjustment

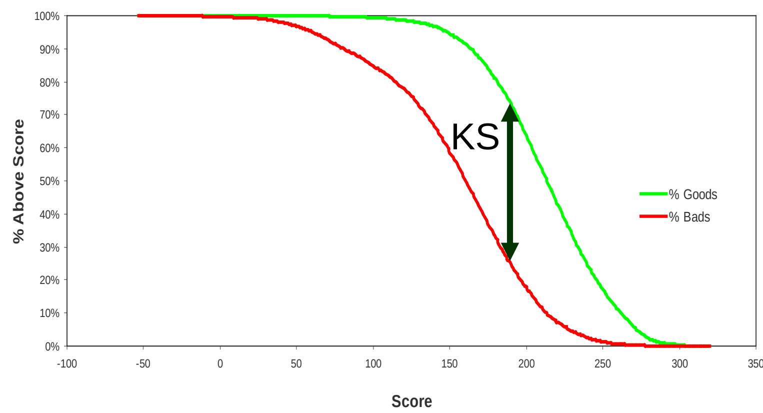
Model Comparison Approach

- For each scorecard and sample, compare
  - Predictive content of criteria
  - ‘Balance’ of scorecards
  - Discrimination, Gini, KS



$$D = 100 \text{ x } \frac{(\mu_G - \mu_B)^2}{\frac{1}{2}(\sigma_G{}^2 + \sigma_B{}^2)}$$





Model Comparison Approach

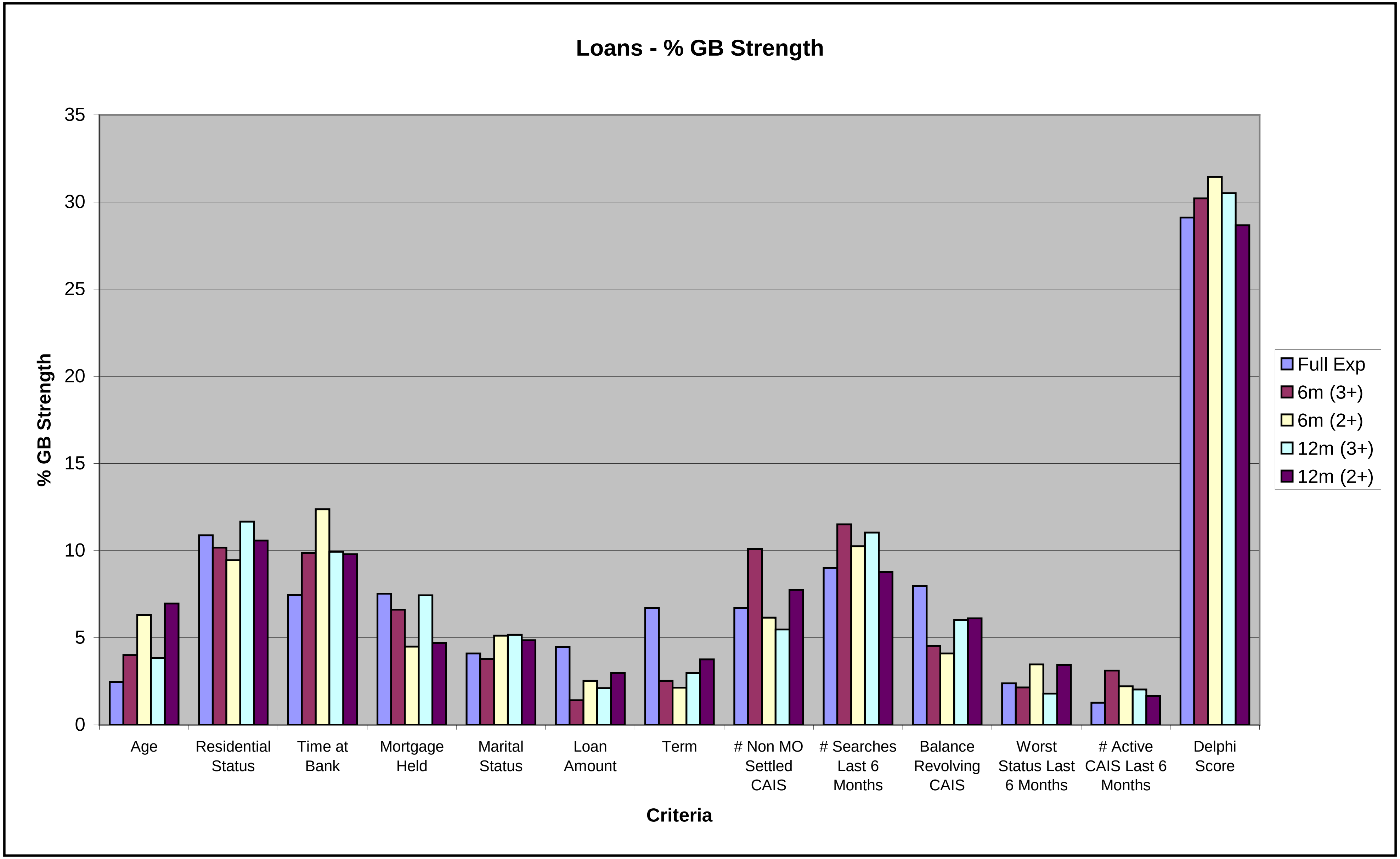
- Assuming that the Full Exposure scorecard and sample were the optimum…
- Note performance of the other models based on the Full Exposure sample
  - Discrimination, Gini, KS
  - Predicted bad rates
  - Profile of accepts

Personal Loans – Scorecard Strength

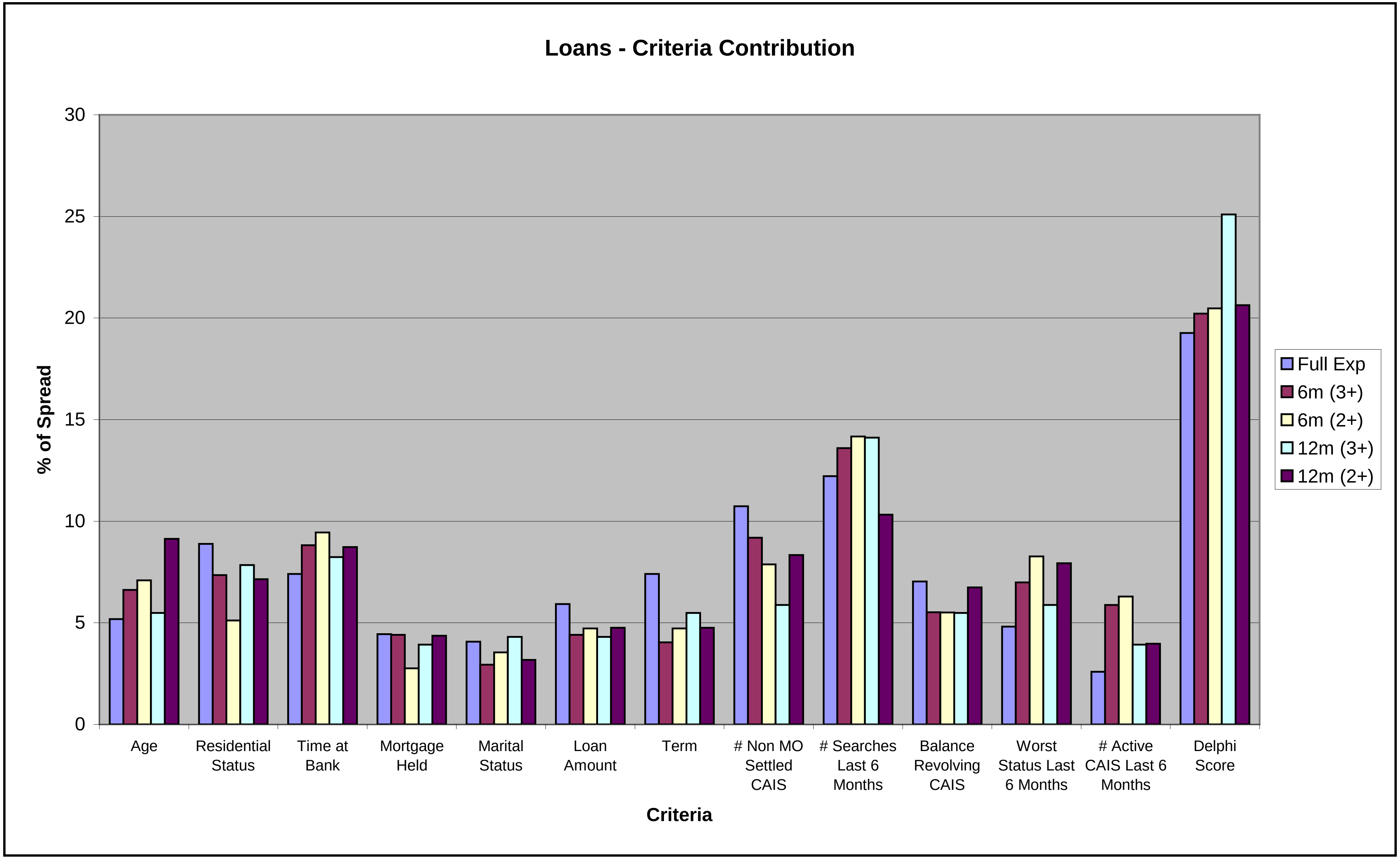
Database	Sample Counts		Discrimination		KS Statistic		Gini Statistic	
33m	Goods	Bads	Own	Fullexp	Own	Fullexp	Own	Fullexp
Fullexp	3063	2989	940	940	38.5	38.5	50.5	50.5
6m (3+)	2925	1521	926	861	37.9	36.5	50.2	48.7
6m (2+)	3013	2165	833	810	36.0	35.5	47.9	47.4
12m (3+)	3016	2312	870	874	36.6	37.8	48.9	49.4
12m (2+)	3014	2993	860	885	36.9	37.3	48.8	49.1

- Based on own sample, 6m(3+) almost as strong!
- Less variation in strength when applied to FullExp
- On FullExp sample,
  - 12m cards lost 6% discrimination
  - 6m(3+) lost 8%

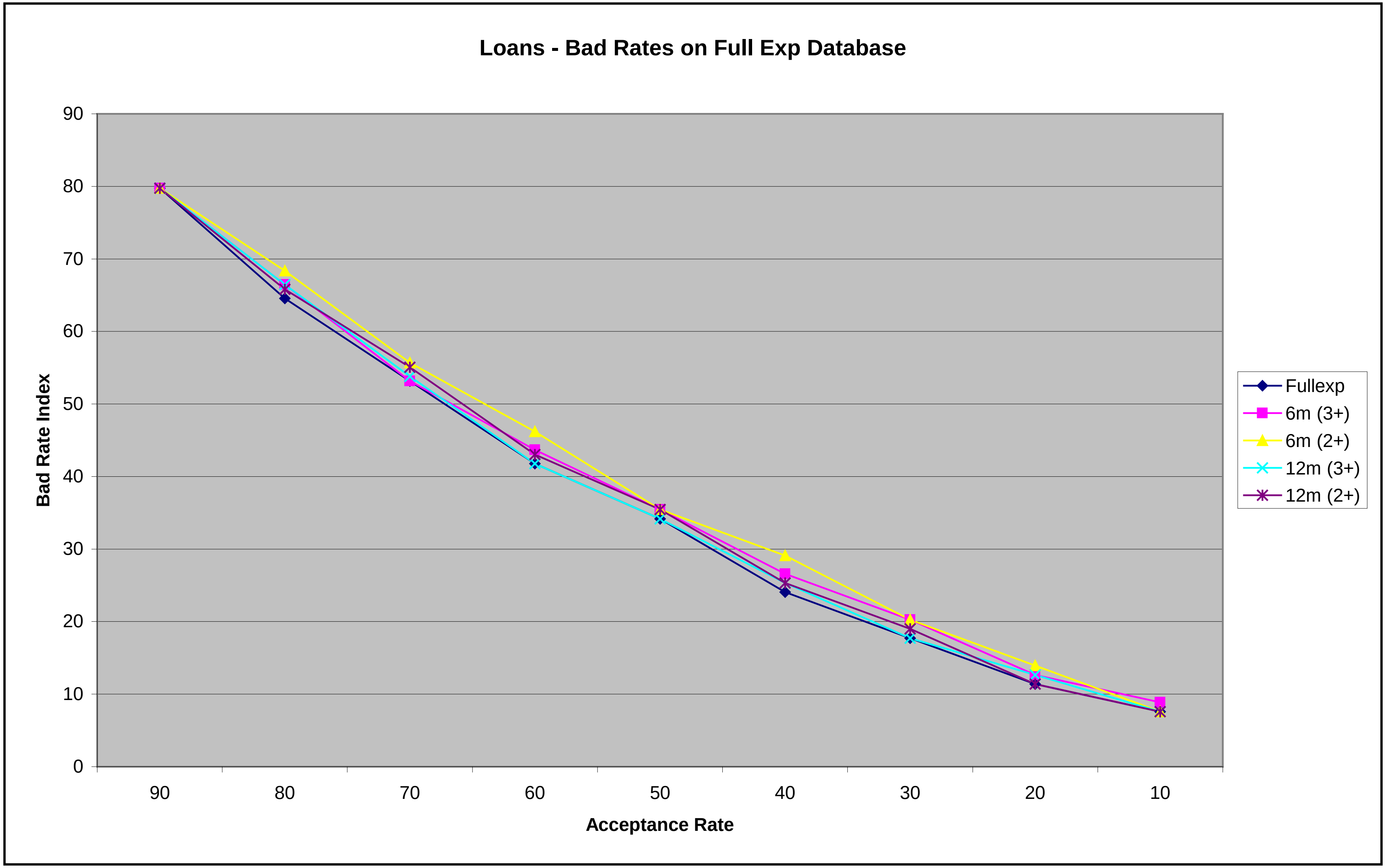
Personal Loans – Criteria Contribution



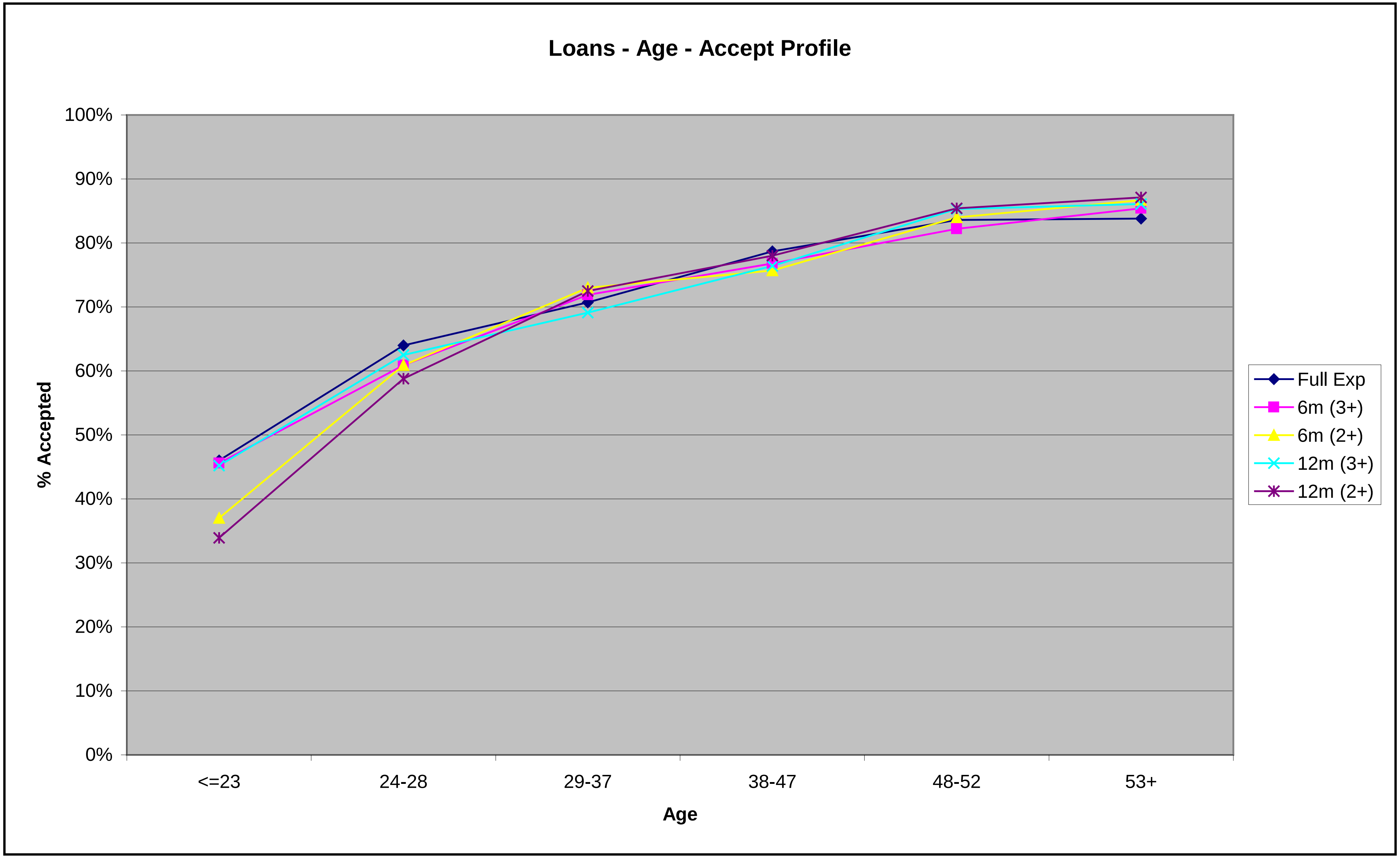
Personal Loans – Criteria Contribution



Personal Loans – Bad Rate Predictions



Personal Loans – Accepted Profile



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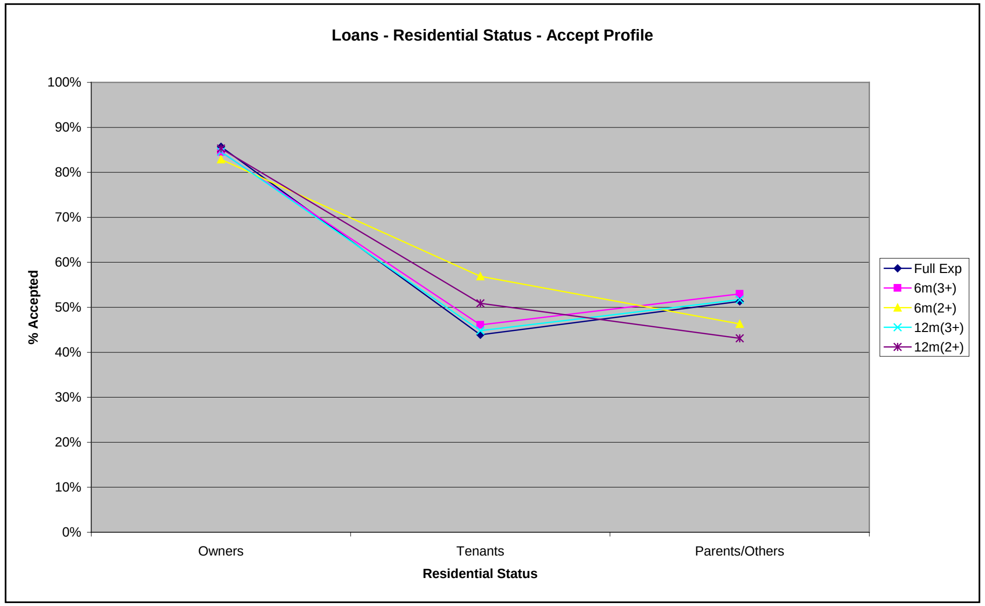
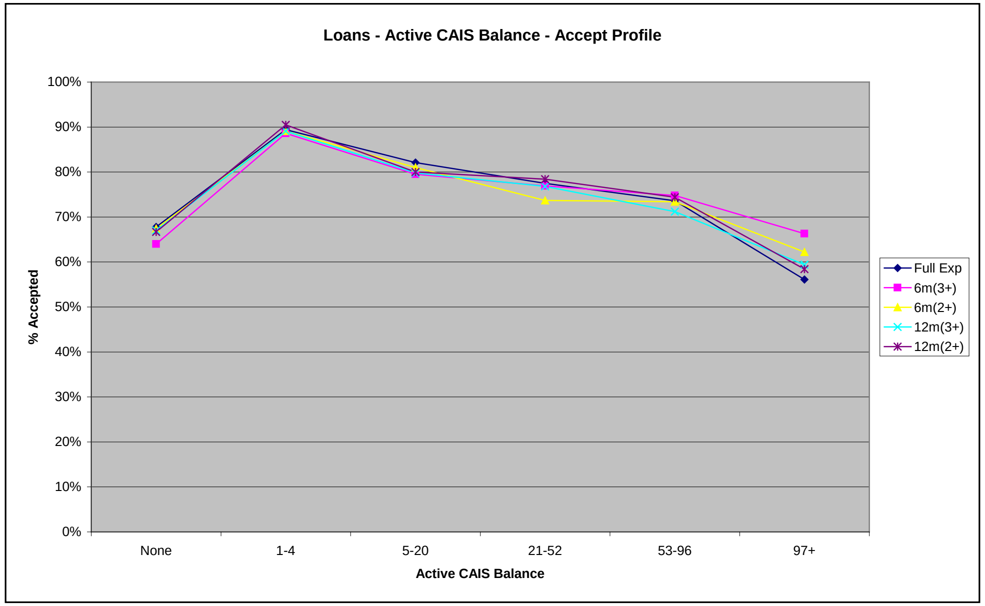
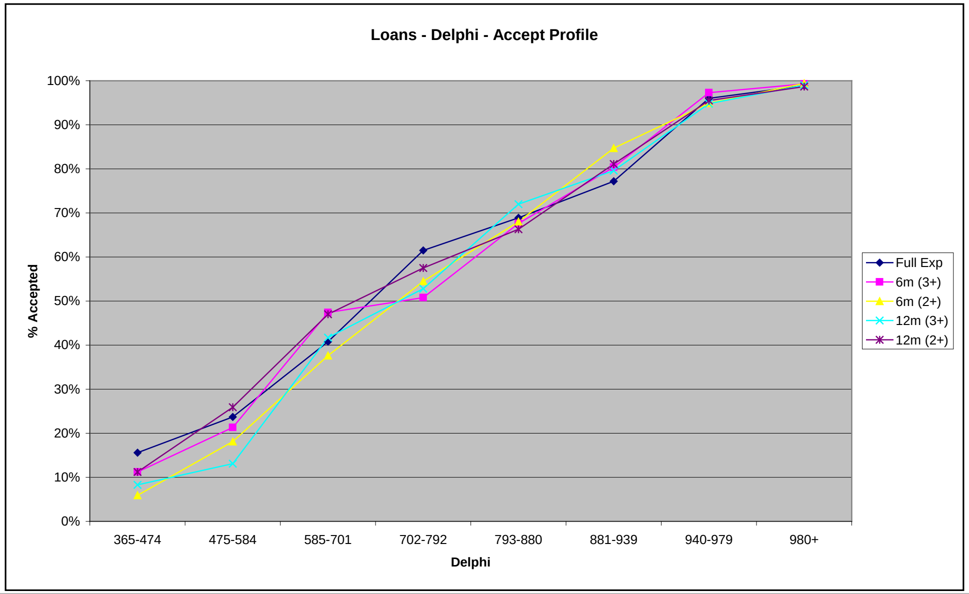






Personal Loans – Summary

- On FullExp sample
  - 12m cards lost 6% discrimination
  - 6m(3+) lost 8%
- Bad rate predictions very similar
- Accepted profiles acceptable
  - especially after experienced adjustment!
- And for the other portfolios…..

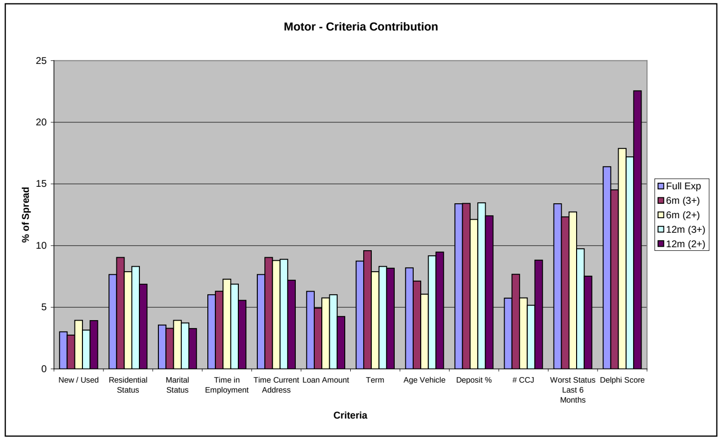
Motor – Scorecard Strength

	Sample Counts		Discrimination		KS Statistic		Gini Statistic	
33m	Goods	Bads	Own	Fullexp	Own	Fullexp	Own	Fullexp
Fullexp	3045	2987	1511	1511	47.8	47.8	61.3	61.3
6m (3+)	2965	2128	1600	1449	48.7	46.4	63.3	60.2
6m (2+)	3053	3002	1496	1469	47.2	47.0	61.2	60.5
12m (3+)	2886	2985	1495	1482	47.7	47.2	60.9	60.7
12m (2+)	2936	3049	1301	1496	44.2	47.9	58.1	61.1

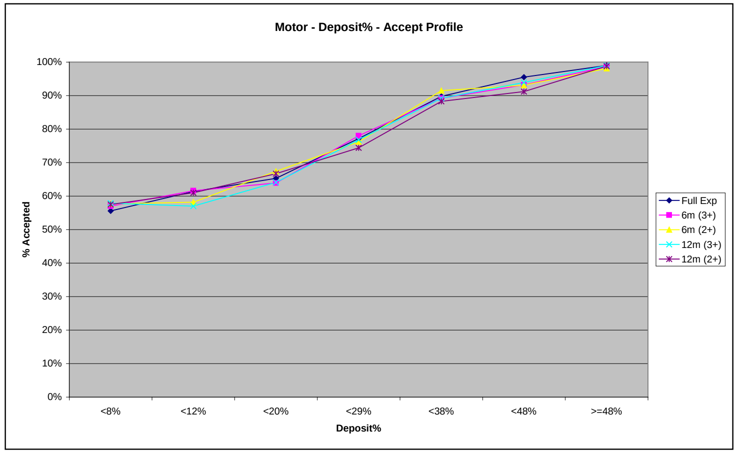
- Based on own sample, 6m(3+) strongest!
- Similar on FullExp
  - 12m cards lost 2% discrimination
  - 6m(3+) lost 4%

Motor – Model Results Comparison

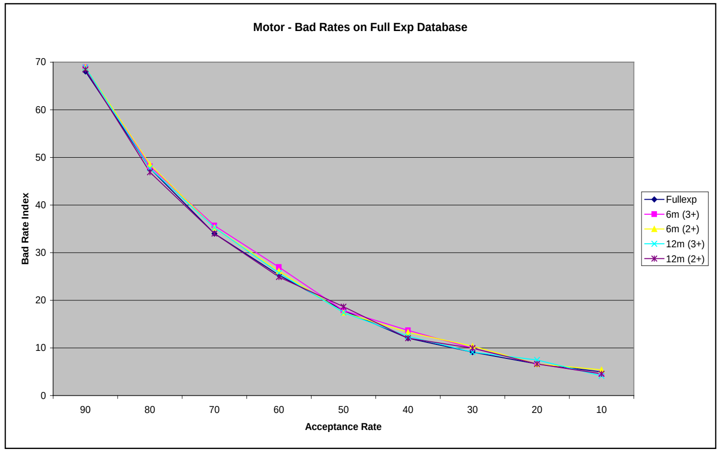
- Small variation in ‘balance’ of scorecards



- Similar accepted profiles



- Same bad rate estimates



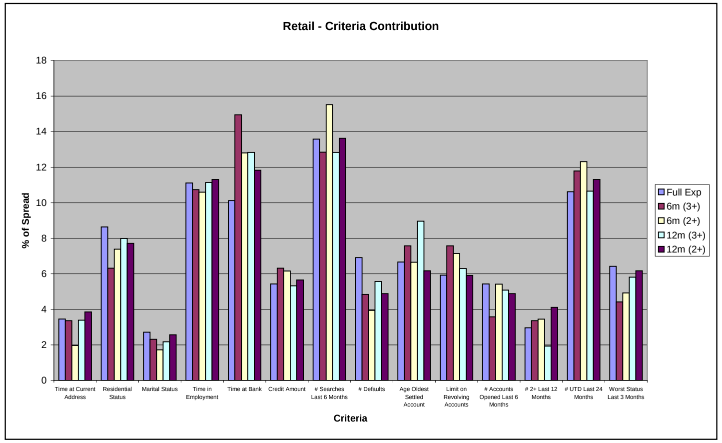
Retail – Scorecard Strength

Database	Sample Counts		Discrimination		KS Statistic		Gini Statistic	
24m	Goods	Bads	Own	Fullexp	Own	Fullexp	Own	Fullexp
Fullexp	2964	3029	2370	2370	57.1	57.1	70.9	70.9
6m (3+)	3074	2368	2762	2248	60.3	55.8	74.5	70.0
6m (2+)	3035	2995	2448	2285	57.0	56.2	71.8	70.1
12m (3+)	2948	2980	2403	2280	57.5	56.0	71.3	70.3
12m (2+)	3046	3027	2106	2264	54.3	56.2	68.3	70.0

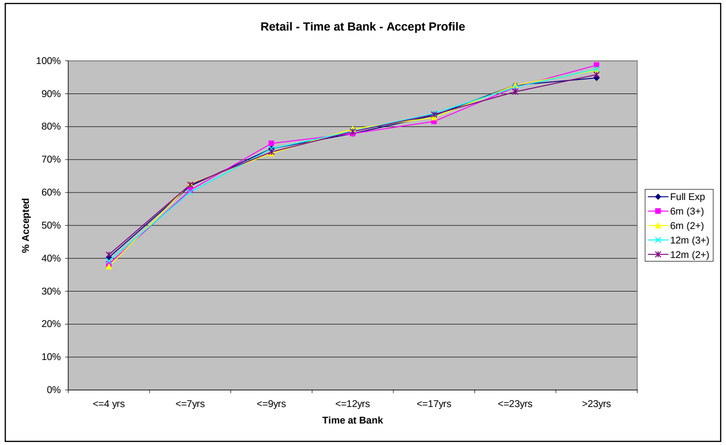
- Based on own sample, 6m(3+) strongest!
- Similar on FullExp
  - 12m(3+) card lost 4% discrimination
  - 6m(3+) lost 5%

Retail – Model Results Comparison

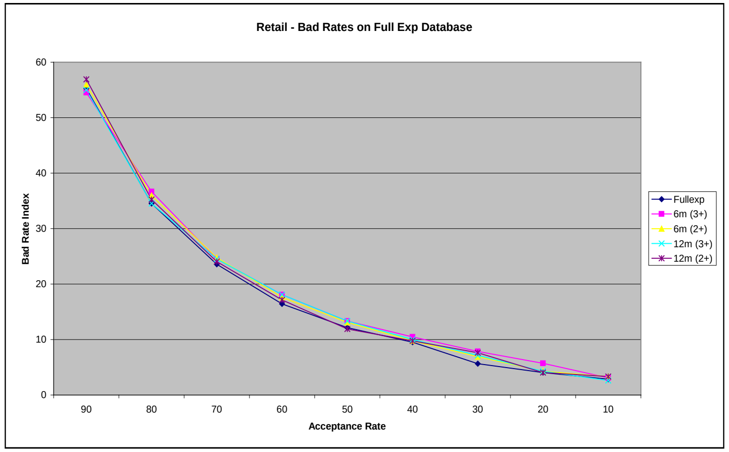
- Small variation in ‘balance’ of scorecards



- Similar accepted profiles



- Very similar bad rate estimates



Mortgages – Scorecard Strength

Database	Sample Counts		Discrimination		KS Statistic		Gini Statistic	
26m	Goods	Bads	Own	Fullexp	Own	Fullexp	Own	Fullexp
Fullexp	3030	411	1576	1576	47.3	47.3	62.1	62.1
6m (3+)	3010	209	1633	1484	49.0	48.4	63.2	61.2
6m (2+)	2978	242	1766	1500	50.9	48.0	65.0	61.5
12m (3+)	2969	310	1669	1570	49.2	48.1	63.4	62.0
12m (2+)	3020	357	1772	1559	50.3	47.4	64.9	62.0

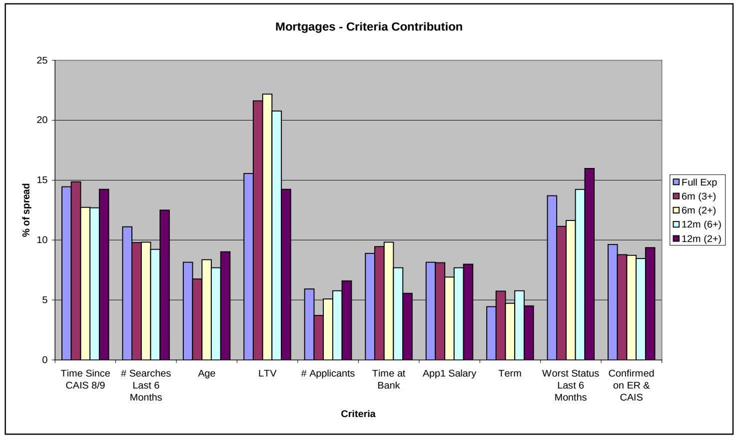
- Very low sample counts
  - even FullExp insufficient for optimum model
  - but comparison still relevant
- Based on own sample, all scorecards stronger than FullExp
  - 2+ stronger than 3+
- Based on FullExp
  - 6m cards lost 6%
  - 12m(3+) & (2+) cards as effective….

Mortgages – Scorecard Strength

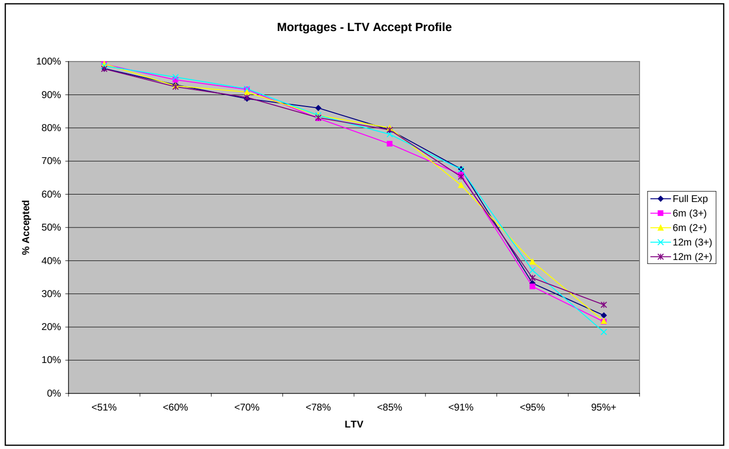
- Attitude to your mortgage
  - Of all your loans – this is your prime concern
  - Try not to miss a payment!
- Therefore
  - 2+ is bad
  - 1 is indicative of problems
  - Adjusted definition is valid

Mortgages – Model Results Comparison

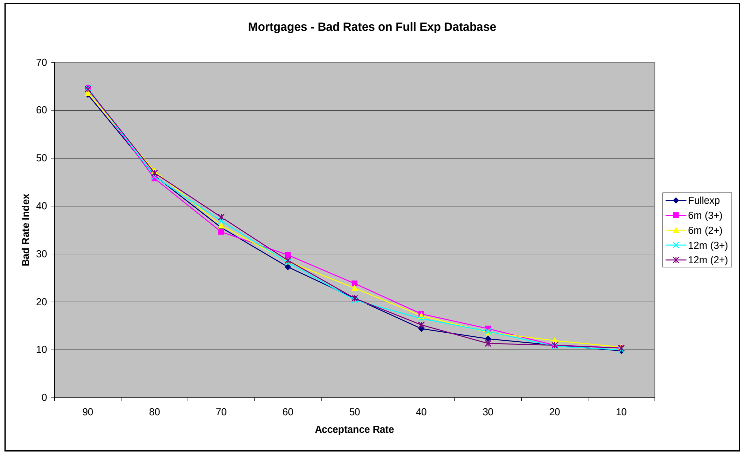
- Small variation in 'balance' of scorecards



- Similar accepted profiles



- Very similar bad rate estimates



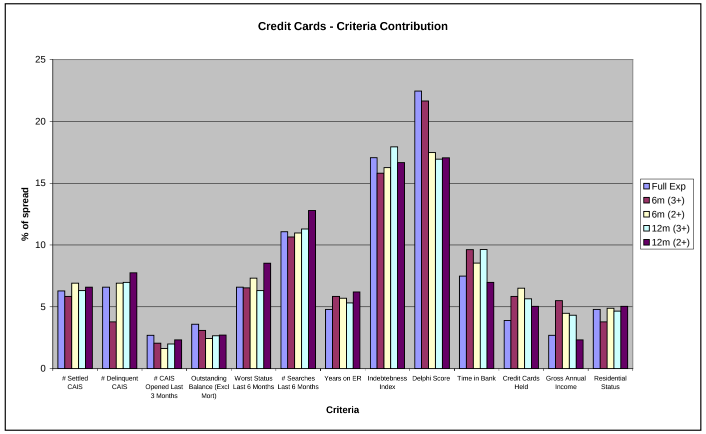
Credit Cards – Scorecard Strength

Database	Sample Counts		Discrimination		KS Statistic		Gini Statistic	
25m	Goods	Bads	Own	Fullexp	Own	Fullexp	Own	Fullexp
Fullexp	3011	1843	1914	1914	52.5	52.5	66.9	66.9
6m (3+)	3062	780	1917	1897	54.4	52.3	66.5	66.2
6m (2+ noind)	2968	1354	1237	1842	44.0	51.1	56.6	65.6
12m (3+)	3028	1342	1838	1912	52.0	52.7	65.7	67.0
12m (2+ noind)	2995	2135	1210	1882	43.2	52.0	56.3	66.4

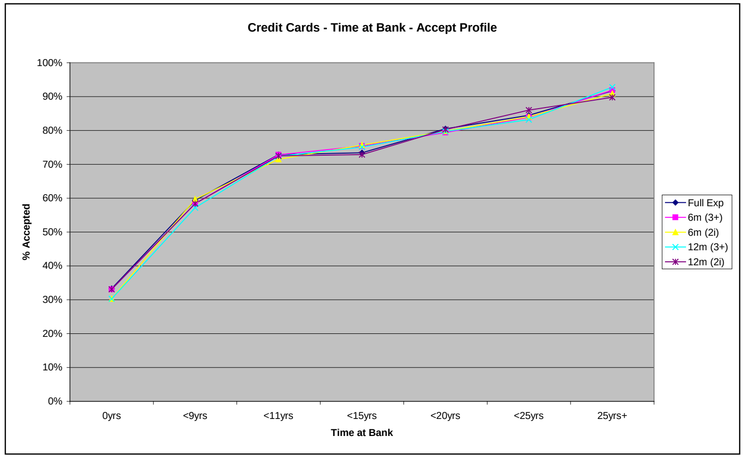
- Based on own sample,
  - 6m(3+) as strong as FullExp
  - 2+ noind much weaker
- Based on FullExp
  - 3+ cards virtually as effective
  - 2+ cards gained in strength

Credit Cards – Model Results Comparison

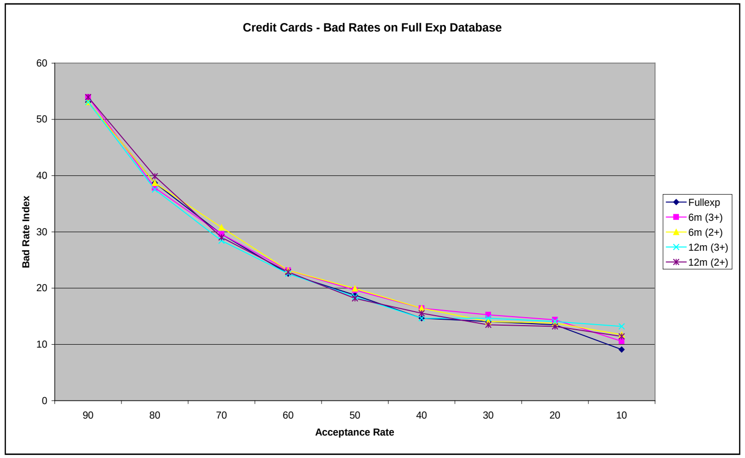
- Small variation in 'balance' of scorecards



- Similar accepted profiles



- Very similar bad rate estimates



Conclusions

- Under-exposed scorecards only marginally less effective
- 6m(3+) cards on average 5% weaker, min 1%, max 8%
- 12m(3+) cards on average 2% weaker, min 0%, max 7%
- Predicted bad rate savings virtually the same
- Accepted profiles very similar

Conclusions

- 2+ definition
- Slight difference in predictive nature
- On own sample
  - generally weaker
  - much weaker for credit cards (no indeterminates)
  - slightly stronger for mortgages!
- Applied to Full Exposure sample
  - nearly as good as 3+ cards

Conclusions

- Little benefit in waiting over 2 years
- But benefit to be gained from Under-Exposure…..
- For generic scorecards
  - earlier access to enhanced bespoke decisions
- Even established scorecard users
  - benefit from a more representative sample
  - avoid archiving or missing data problems
  - faster fine-tunes
- Monitor at an early stage
  - or factor up to ultimate bad rates
- So why wait? Let's get….

Under-Exposed!

Gaynor Bennett