

# Scoring Models for Collections & Debt Recovery

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# Introduction

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- Why do we need collections / recovery scores?
  - ▶ Due to difficult financial conditions more people are going into arrears
  - ▶ Optimising the use of collections resources is therefore key
  - ▶ The use of collections scores facilitates the automation of a number of collections activities
  - ▶ Account level scores achieve this reasonably well but a more holistic approach offers a marked improvement
  
- Targeting the best prospects for debt recovery can also be automated

# Agenda

- High Level Overview
- Collections
- Debt Recovery (Charge-Off's)
- Summary

# High Level Overview

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- Investigated 2 main areas
  - ▶ Tools to improve the management of accounts in collections across a range of financial products
  - ▶ Tools to highlight the best prospects for debt recovery action
- Show how each solution has evolved
- Illustrate the power of consumer level data in collections / debt recovery

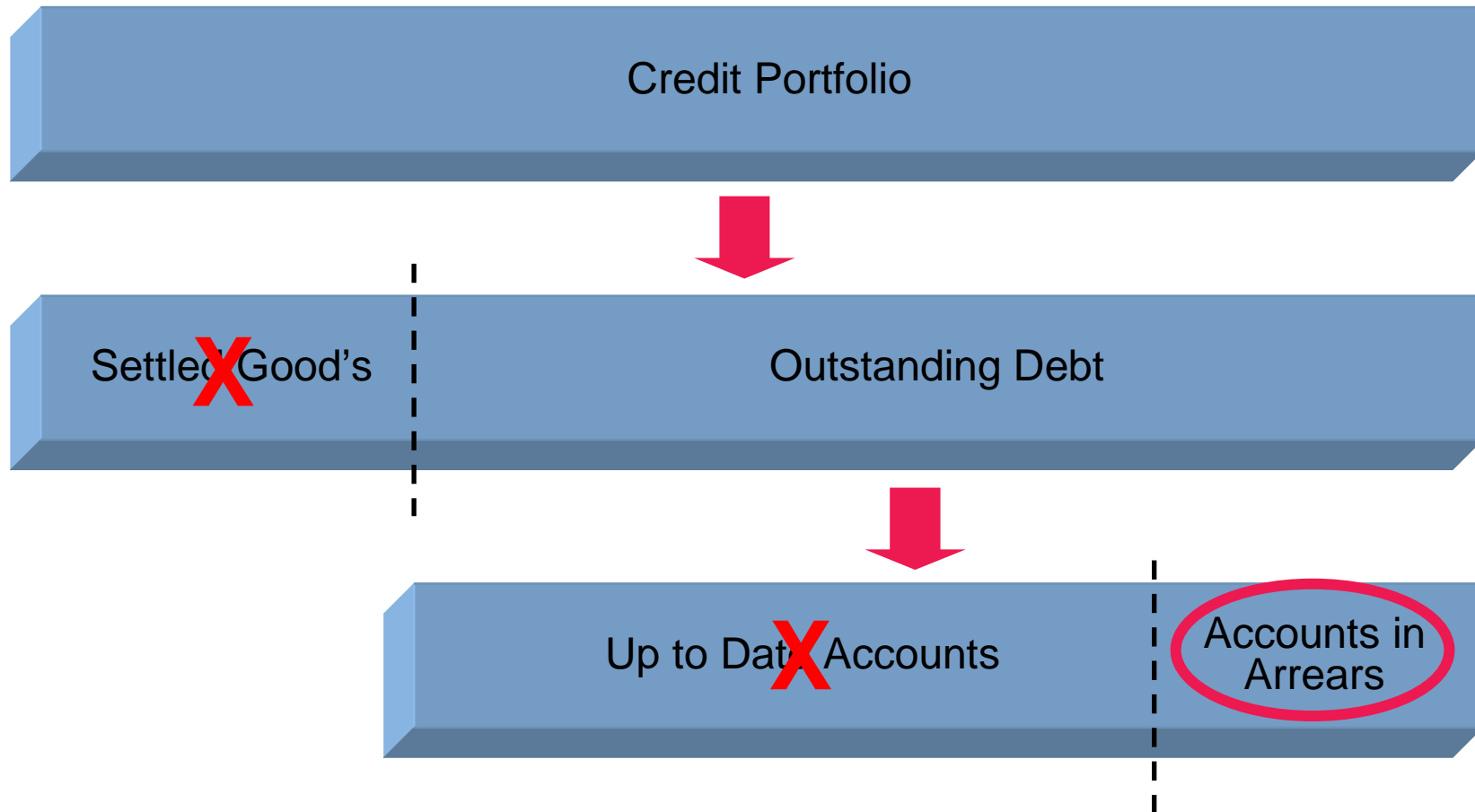
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# Collections

## *Identifying development samples*



# Collections *Objectives*

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- Determine the probability an account in arrears will make further payments in order to determine the most appropriate collections path
  
- Objective function is therefore:
  - ▶ Goods:       At least one (minimum) payment received in the 3 months following observation and account does not default during outcome
  
  - ▶ Bads:        Not Good
  
- For Communications accounts the good / bad definition is generally harsher to reflect the industry view of accounts in arrears

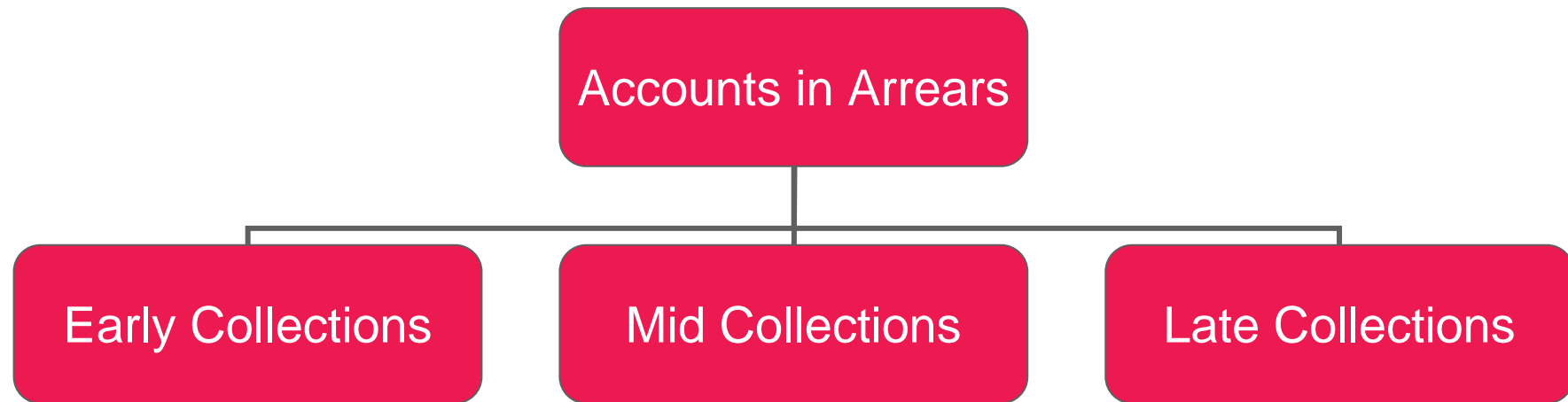
# Collections Segmentation

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- For the active element of the portfolio which is in arrears there will be a range of profiles that make applying a single solution difficult
- These range from slow payers who normally are up to date to accounts in serious financial difficulty
- These profiles will behave differently across credit products
- Further segmentation is therefore required to build an effective collections score
  - ▶ *You don't want to put a good payer who has simply forgotten to pay the bill through an intensive collections path*

# Collections Segmentation

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- Early collections includes “target accounts” 30 days past due
- Mid collections would be 60-90 days past due (60 dpd for Communications)
- Late Collections are 120 days past due (90 dpd for Communications)

# Collections

## *Sample profiles*

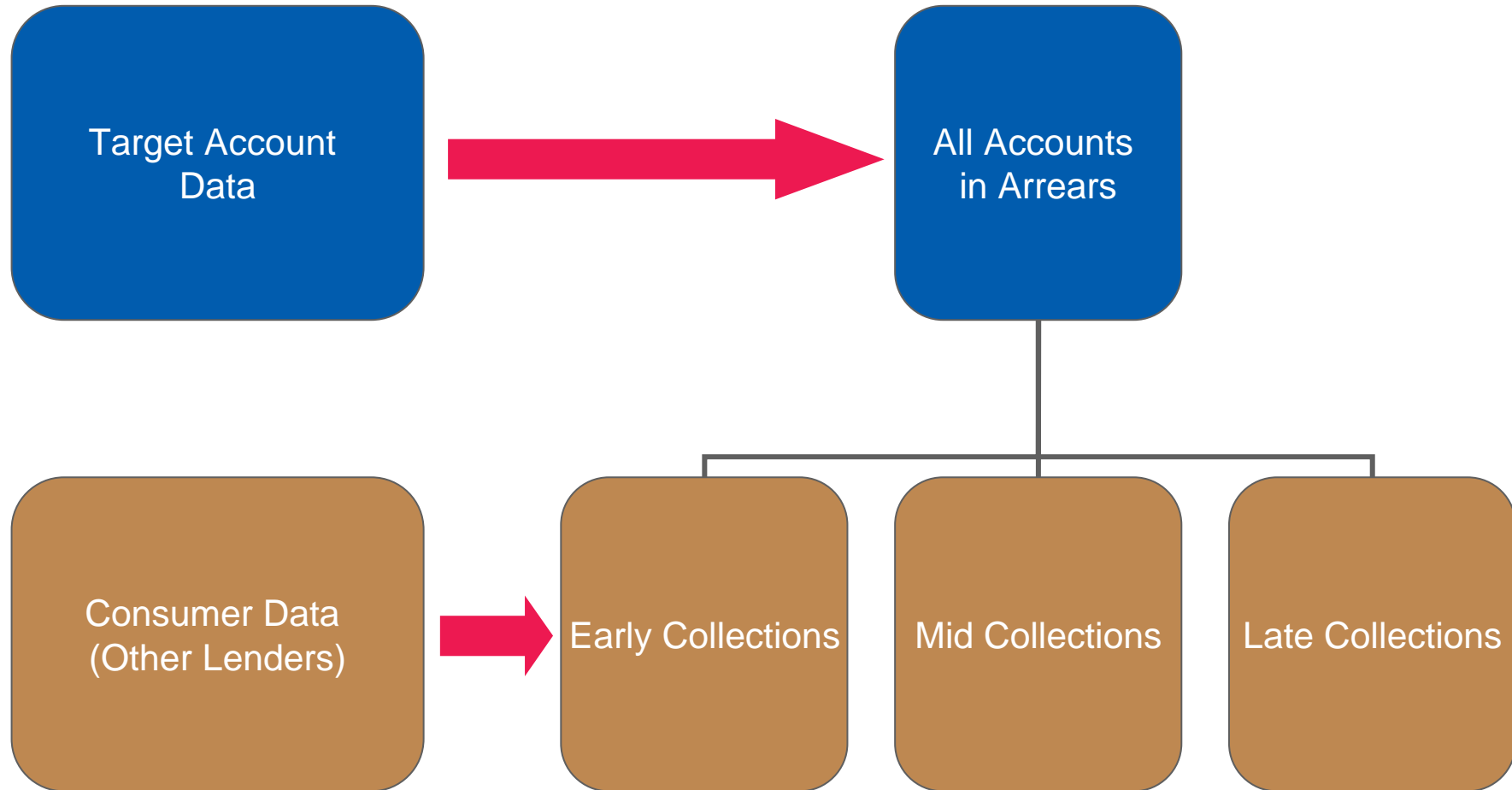
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<b>Good / Bad Odds</b>	<b>Early</b>	<b>Mid</b>	<b>Late</b>
Communications	1.04	0.41	0.12
B&F (Unsecured)	5.08	1.02	0.37
Retail	12.24	2.40	0.98
B&F (Secured)	15.40	4.85	1.71

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# Collections

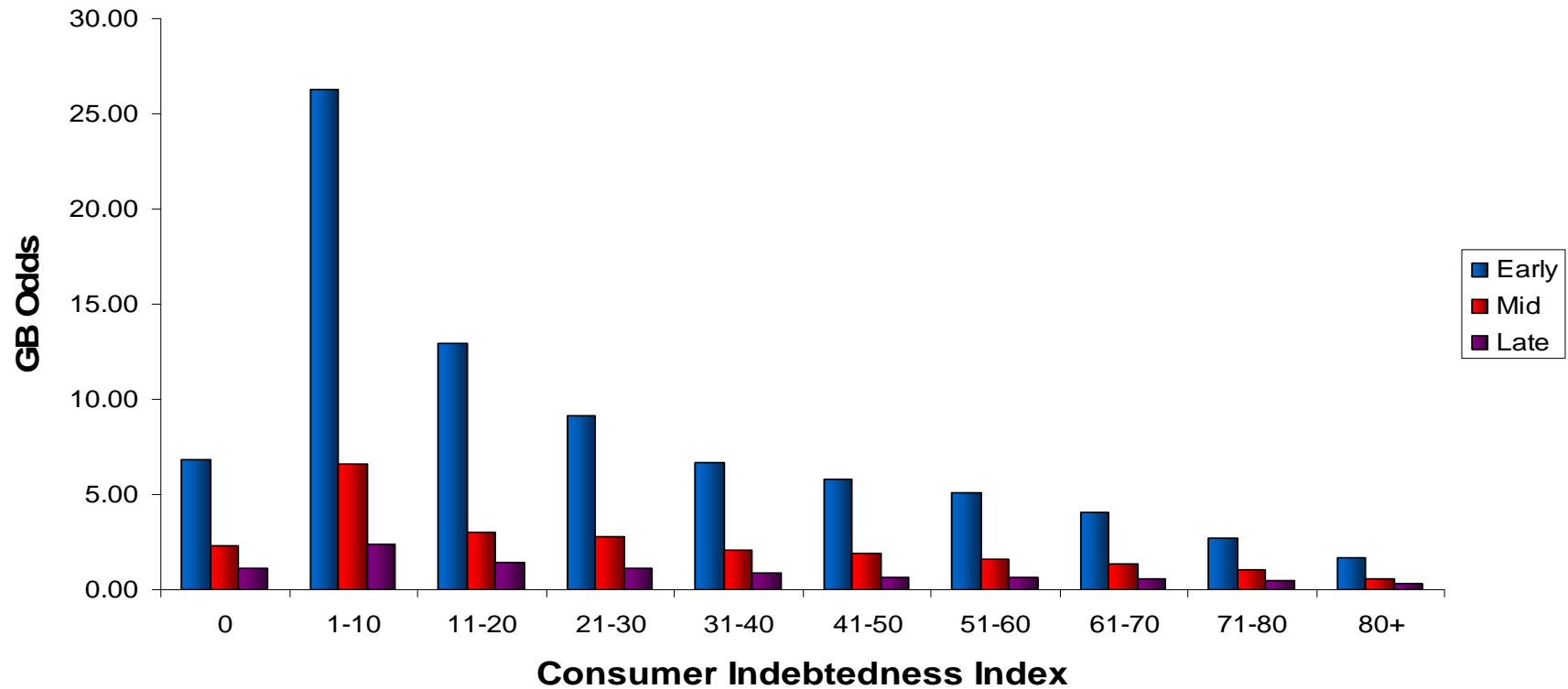
## *Combining client / consumer data*



# Collections

## Key predictors – Financial services

Financial Services - Key Predictors

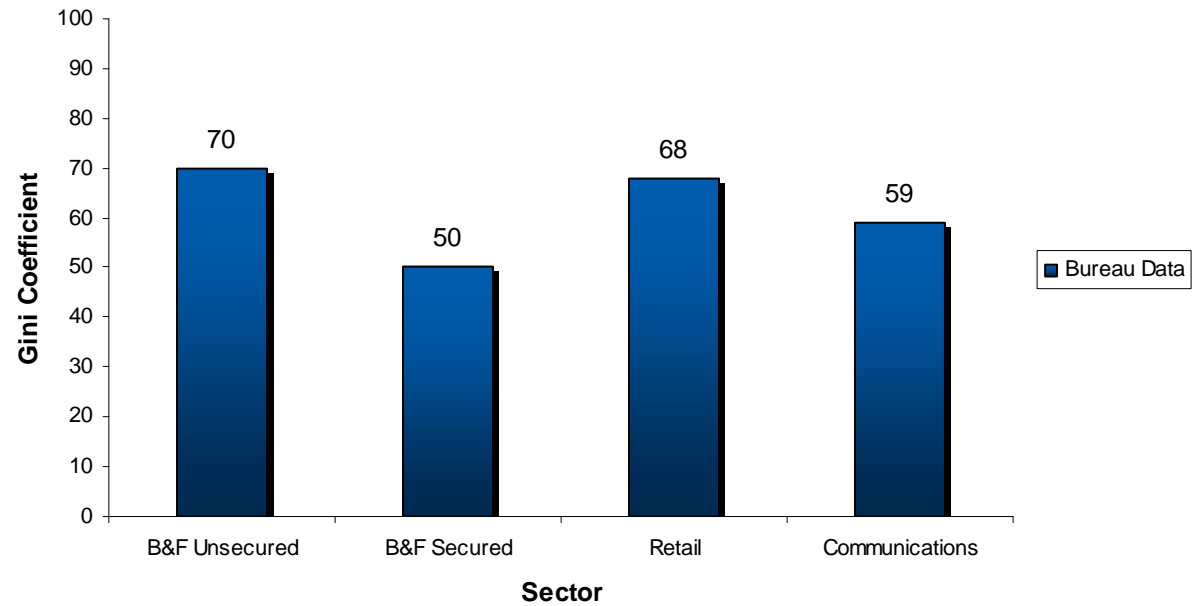


# Collections

## *Building a solution*

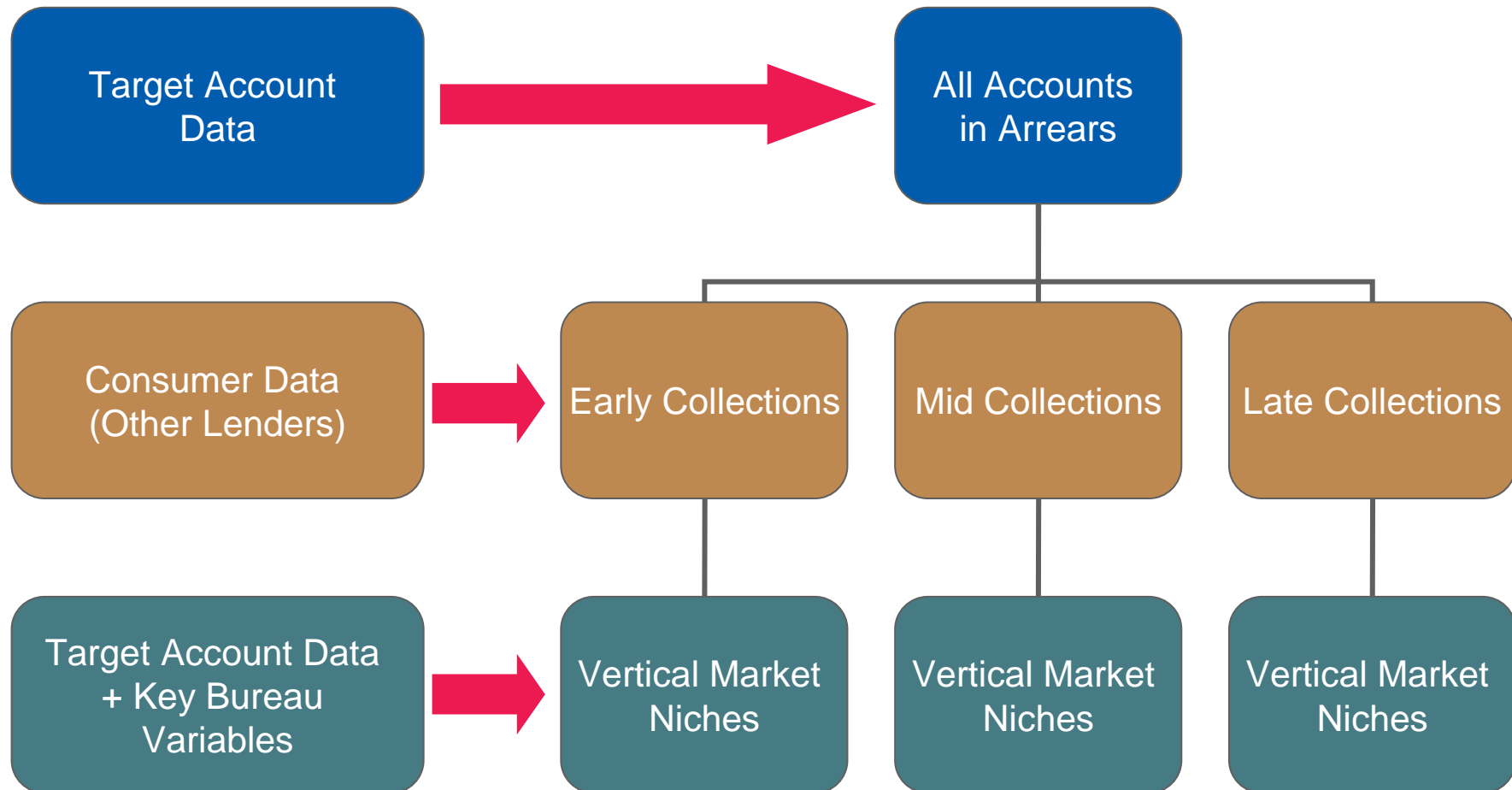
- Results from Bureau only contribution

Performance of Collections Scorecards



# Collections

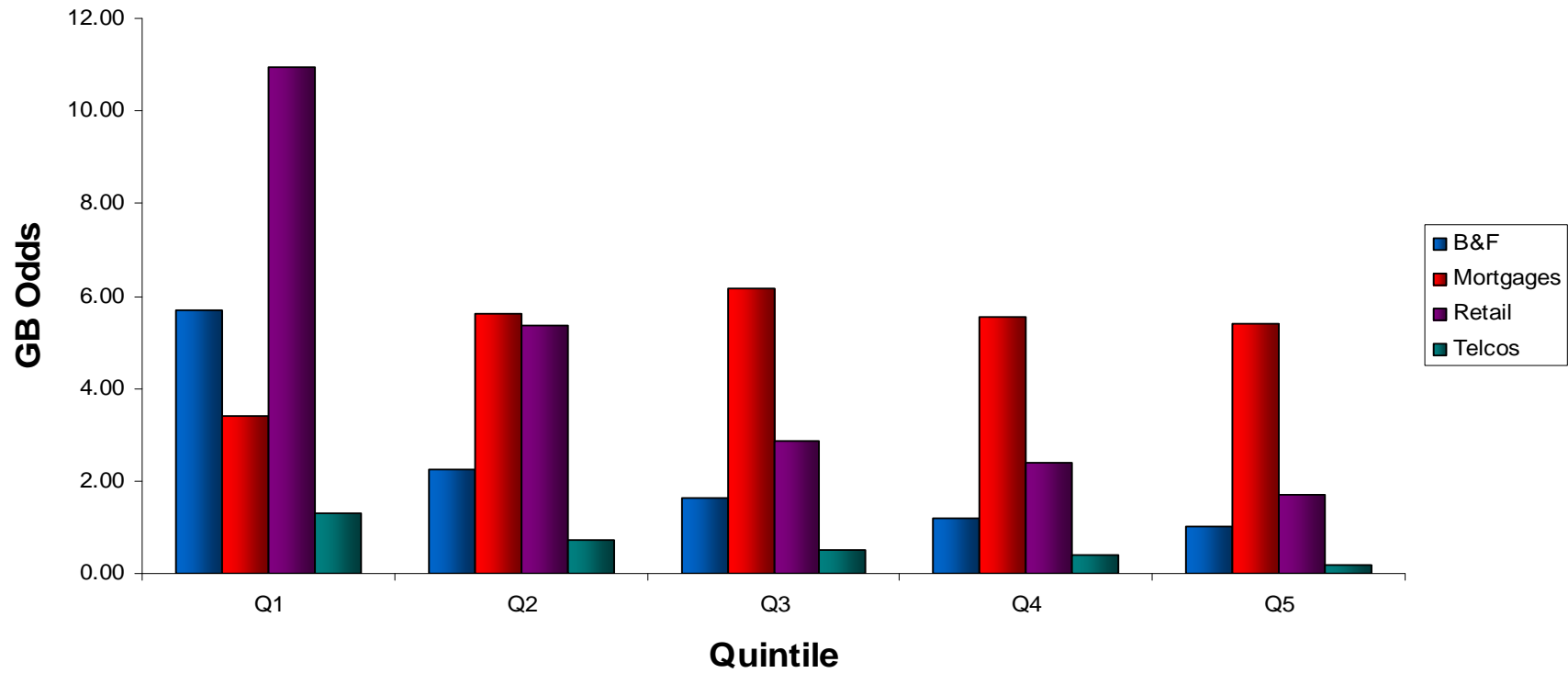
## *Combining client / consumer data*



# Collections

## Key predictors

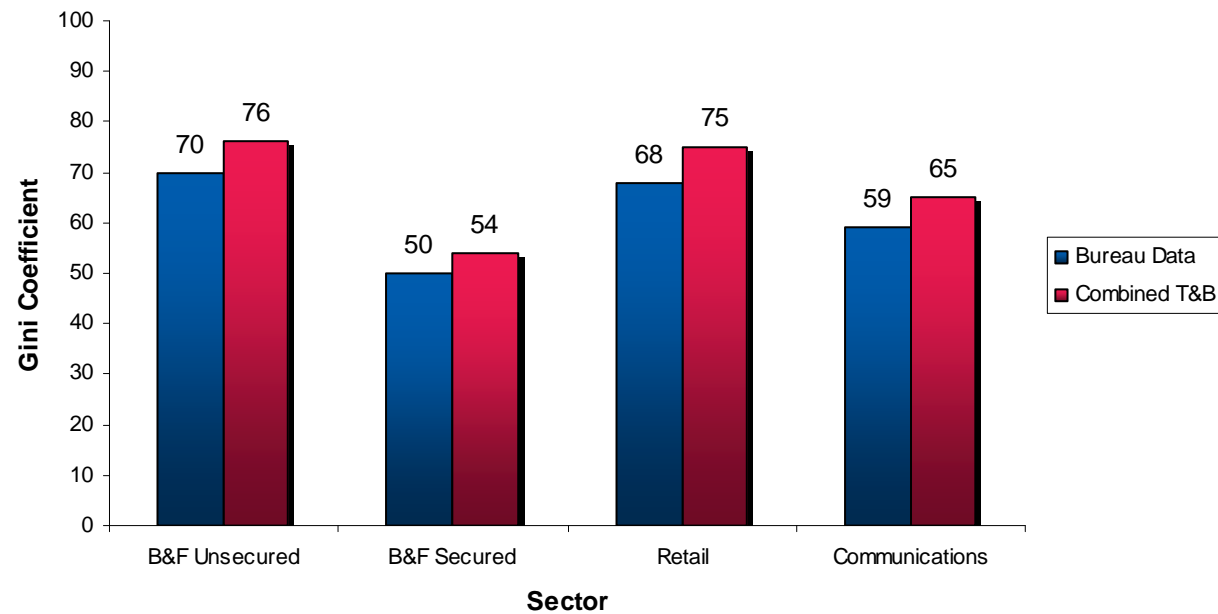
### Observation Balance



# Collections Performance

- Results from Combined Bureau + Target Account contribution

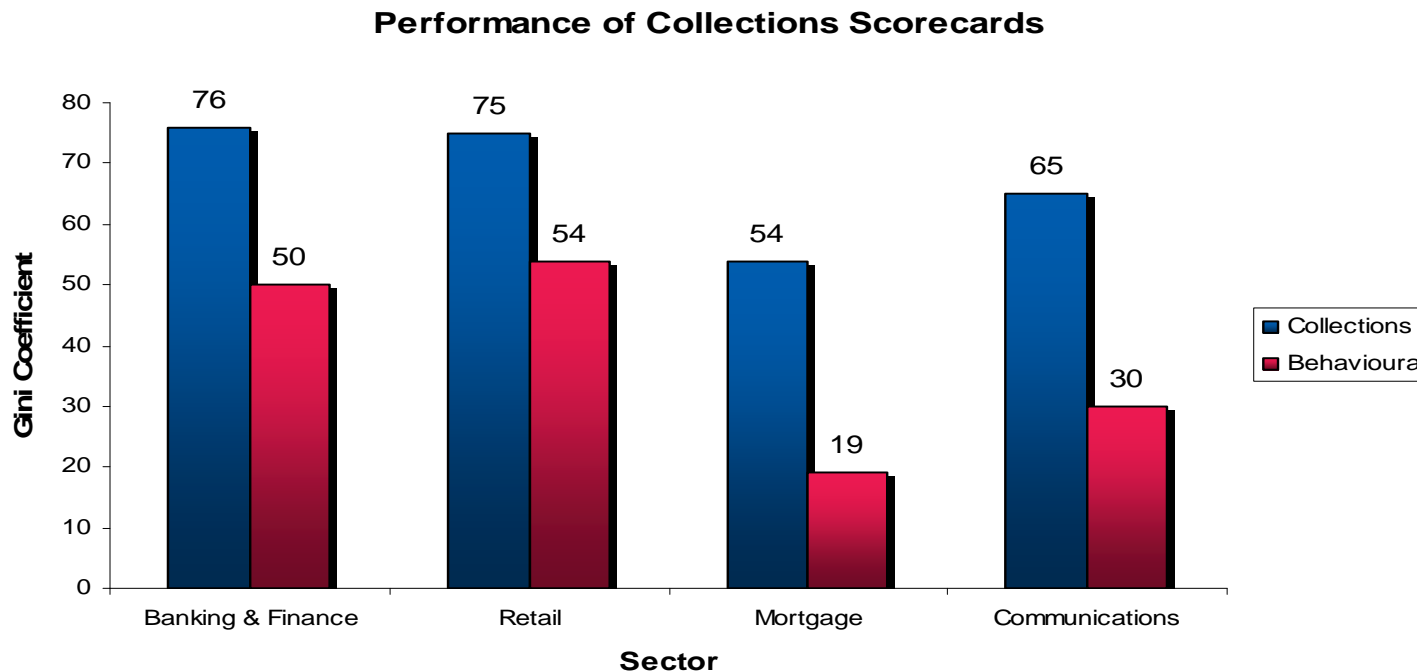
Performance of Collections Scorecards



# Collections

## *Comparison to generic, all purpose behavioural score*

- The large uplift over the generic behavioural score illustrates the importance of utilising a score based on collections specific predictors & performance



# Collections

## *Limitations of generic collections scores*

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- Clearly collections specific scores are much more effective than using a standard behavioural score
  
- Bureau data is very powerful when combined with account level data for use in collections
  
- However, generic collections scores cannot take into account
  - ▶ Client specific account performance
  
  - ▶ The effectiveness of each clients own collections departments

# Collections

## *Bespoke collections scoring*

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- Here the overall objective is to build a bespoke consumer collections score derived on client data
- Combine the power of specific external data with a lenders internal data
- Derived using similar Early, Mid & Late collections segmentation
- In addition to the usual bureau variables a few new ones were generated looking solely at the recent performance of other accounts in collections
  - ▶ Number of accounts in collections
  - ▶ Number which have received a recent payment
  - ▶ Number which have received a significant recent payment

# Collections

## *Bespoke collections scoring - Results*

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GINI	Generic Collections Score	Bespoke Collections Score
All	45.5	52.9
Early	41.5	50.6
Mid	33.9	42.8
Late	31.7	41.5

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- The existing scores performed considerably worse than either the generic or bespoke collections solutions above

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# Debt Recovery (Charge-Off's)

## *Objectives*

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- These are typically non-paying accounts with Debt Collection Agencies (DCA's) that can also be passed back to the original lender for further action
  
- Focus on non-paying / dormant debt where the objective is to identify which individuals are likely to repay some or all of the balance owed
  
- Objective Function is therefore
  - ▶ Goods: Any payment received in the next month
  - ▶ Bads: No payment received within the next month
  - ▶ Exclusions: Forwarding address located

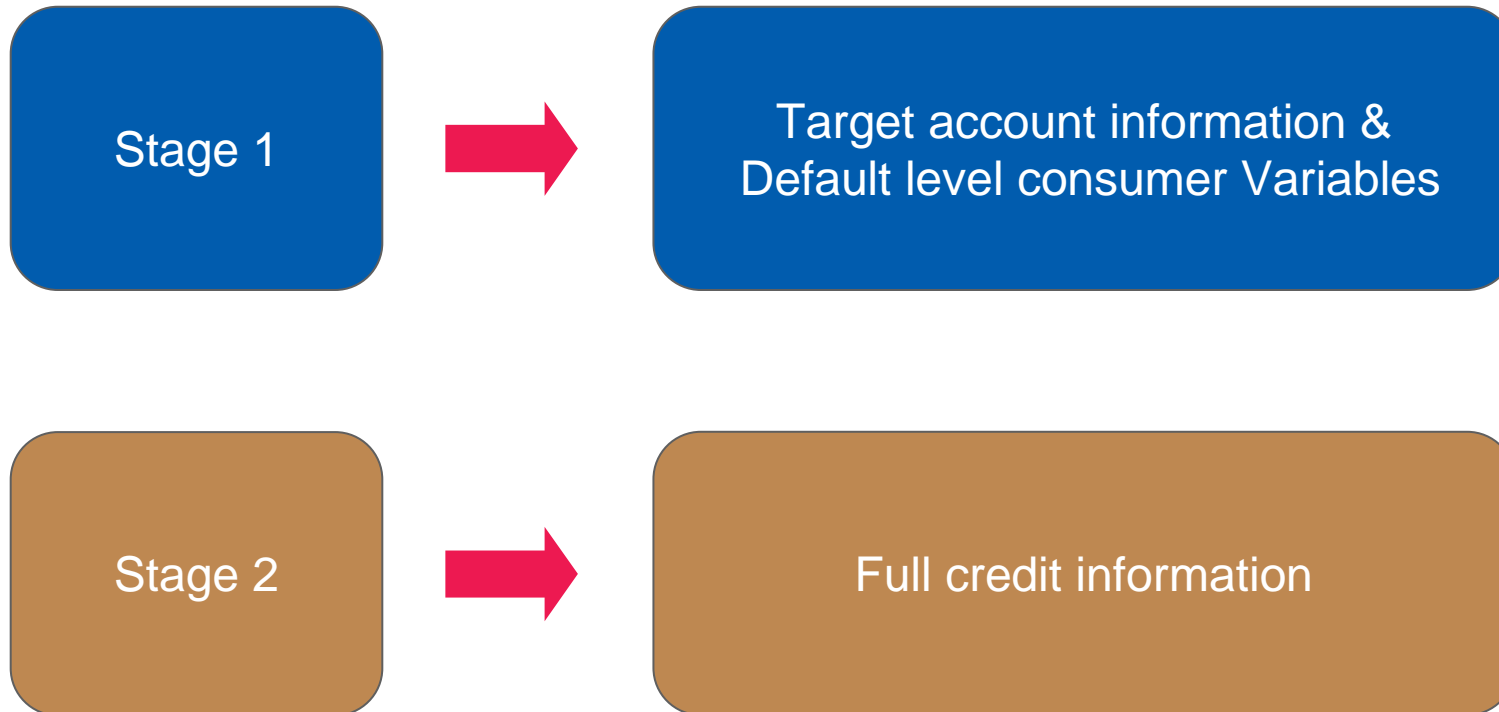
## Debt Recovery (Charge-Off's) *Segmentation / sample composition*

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- Sample of credit defaults from multiple DCA's
- No segmentation applied for initial investigations
- Sample G/B odds equate to 0.14

## Debt Recovery (Charge-Off's) *Combining client / consumer data*

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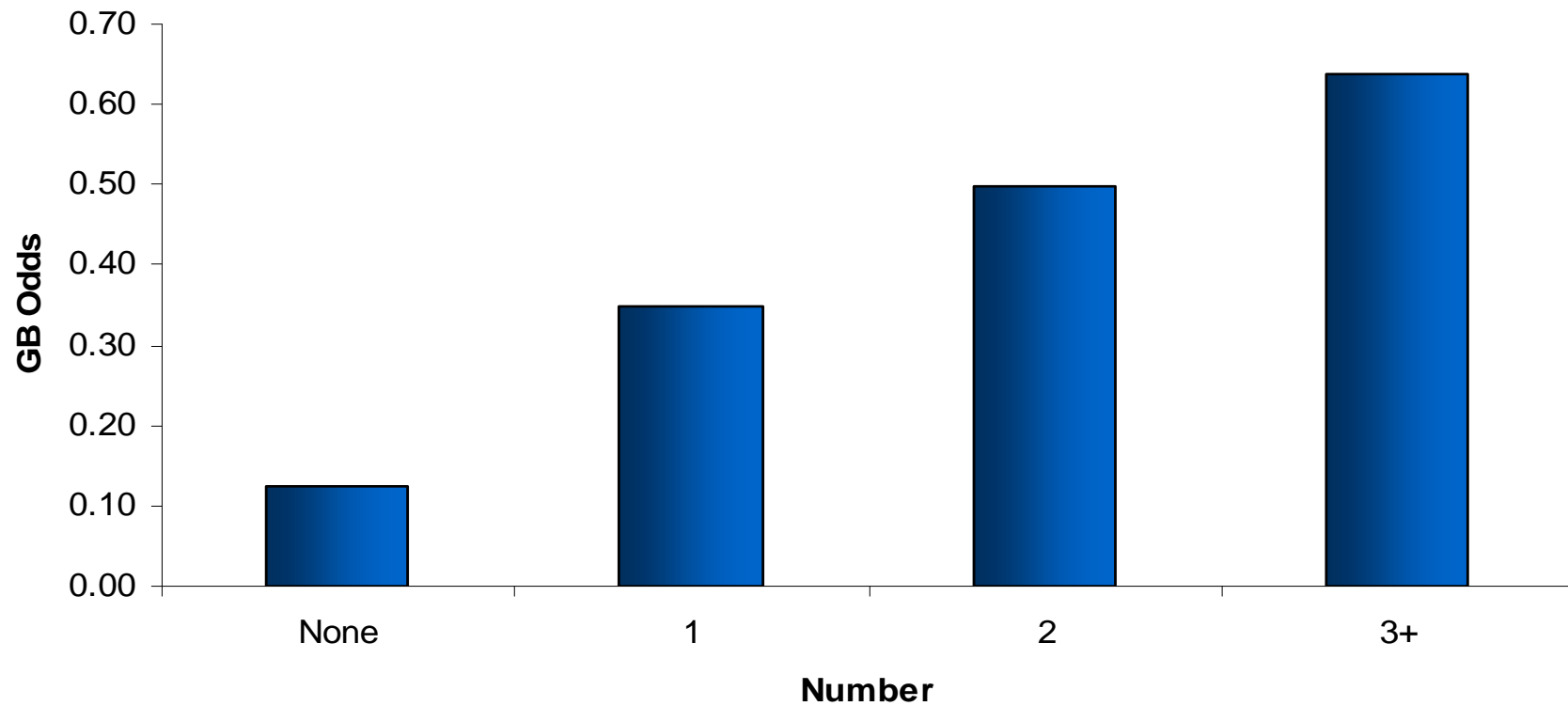


# Debt Recovery (Charge-Off's)

## *Key predictors*

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Number of Paid Up Defaults L12M

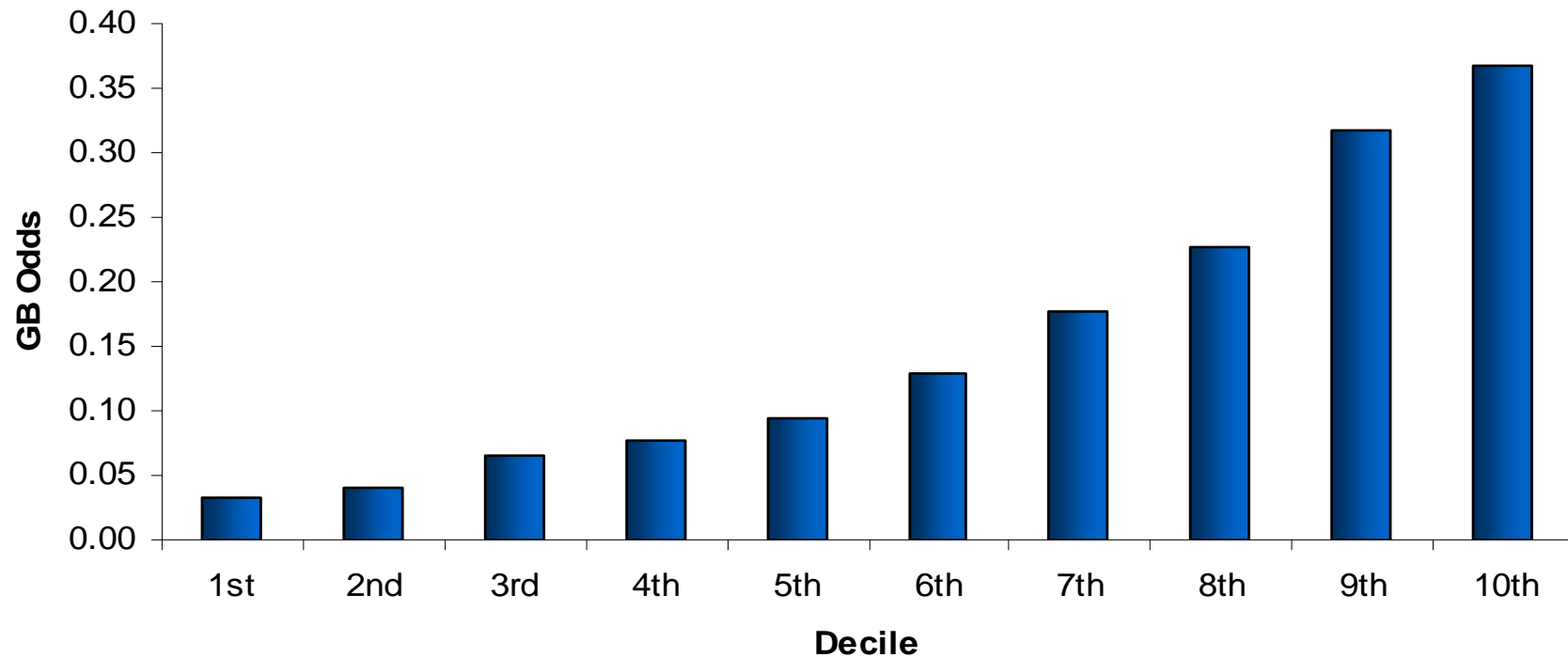


# Debt Recovery (Charge-Off's)

## *Key predictors*

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**Original Default Balance**  
*Low - High*



## Debt Recovery (Charge-Off's) Score *Distribution*

Score Decile (Low to High)	Propensity to Pay
1st	0.57%
2nd	1.07%
3rd	1.35%
4th	2.19%
5th	3.32%
6th	4.33%
7th	9.51%
8th	19.52%
9th	34.57%
10th	55.48%
Overall	12.00%

- Initial results produced GINI figures in excess of 75 for a score using combined client and consumer level default data

## Debt Recovery (Charge-Off's) *Using a DR Score*

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- The resulting score can be used to target the top X% of the population for additional debt recovery action
- Such a score can be delivered relatively easily in a batch environment that monitors an individuals credit profile to detect signs of improvement
- Experian's batch scoring system also indicates where an individual in debt recovery has changed address

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# Summary

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- Account level information is limited in predicting collections (and debt recovery) success
- A more holistic solution provides a significant uplift
- This is even greater when a client specific model is developed
- A bureau based collections / debt recovery approach can greatly simplify the overall solution



# Experian

A world of insight

